UNIVERSITÉ DU QUÉBEC À MONTRÉAL

ANALYZING AND CLASSIFYING GROUP DYNAMICS DYSFUNCTIONS IN INTERPERSONAL DIALOGUES

DISSERTATION

PRESENTED

AS PARTIAL REQUIREMENT

TO THE MASTERS IN MASTER OF COMPUTER SCIENCE

BY

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Abstract

Nowadays, team members communicate online to work and communicate, relying on several applications such as ZOOM, WhatsApp, and MS Teams. This change has led to team meetings taking place online (virtually) rather than in person. Partners communicate via voice messages, video calls, or text conversations (dialogues). Some problems have been observed with virtual teamwork (lam et al, 2005). In this study, our main goal is to identify the five dysfunctions in dialogues. Specifically, we focus on a type of analysis called "sentiment analysis." We want to train a machine learning model that learns the five dysfunctions with the intensity level of each (low, medium, and high). Research on these datasets has been unsuccessful. Therefore, we built our dataset using ChatGPT. This task aligns with the principles of supervised learning, where models are trained on labeled data sets to distinguish patterns and relationships between provided features and assigned dysfunction levels. The model can then predict the dysfunction level of new cases, providing a valuable mechanism for addressing teamwork dysfunctions. Four distinct machine learning algorithms were used to train the model with the generated datasets. Support Vector Machine (SVM), Logistic Regression, Naïve Bayes, and Random Forest. These algorithms learn from labeled data to recognize patterns and make predictions on new, unseen data. The results show how machine learning models can identify and categorize teamwork dysfunctions based on Lencioni's model (Lencioni, 2015). For each of the five dysfunctions, average accuracy scores were calculated for low, medium, and high levels. The results show difficulties in classifying moderate cases, whose accuracy is often lower than the low and high levels for all dysfunctions. We are reasonably confident that ChatGPT or similar technologies provide a viable methodology to generate the desired dataset, provided that we can improve the generation of dialogs and formally validate the quality of the generated dataset.

UNIVERSITÉ DU QUÉBEC À MONTRÉAL

ANALYSER ET CLASSIFIER LES DYSFONCTIONNEMENTS DE LA DYNAMIQUE DE GROUPE DANS LES DIALOGUES INTERPERSONNELS

MÉMOIRE

PRÉSENTÉ

COMME EXIGENCE PARTIELLE

DE LA MAÎTRISE EN INFORMATIQUE

PAR

YASMEEN WALID ABUHASIRAH

OCTOBRE 2024

Résumé

De nos jours, les membres d'une équipe communiquent en ligne pour travailler et communiquer, en s'appuyant sur plusieurs applications comme ZOOM, WhatsApp et MS Teams. Ce changement a conduit à ce que les réunions d'équipe se déroulent en ligne (virtuellement) plutôt qu'en personne. Les partenaires communiquent via des messages vocaux, des appels vidéo ou des conversations textuelles (dialogues). Certains problèmes ont été observés avec le travail en équipe virtuel (lam et al, 2005). Dans cette étude, notre objectif principal est d'identifier les cinq dysfonctionnements dans les dialogues. Plus précisément, nous nous concentrons sur un type d'analyse appelé « analyse des sentiments ». Nous souhaitons former un modèle d'apprentissage automatique qui apprend les cinq dysfonctionnements avec le niveau d'intensité de chacun (faible, moyen et élevé). Les recherches sur ces ensembles de données se sont révélées infructueuses. Nous avons donc construit notre ensemble de données en utilisant ChatGPT. Cette tâche s'aligne sur les principes de l'apprentissage supervisé, où les modèles sont formés sur l'ensemble des données étiquetées pour distinguer les modèles et les relations entre les fonctionnalités fournies et les niveaux de dysfonctionnement attribués. Le modèle peut ensuite prédire le niveau de dysfonctionnement de nouveaux cas, offrant ainsi un mécanisme précieux pour résoudre les dysfonctionnements du travail d'équipe. Quatre algorithmes d'apprentissage automatique distincts ont été utilisés pour entraîner le modèle avec les ensembles de données générés. Machine à vecteurs de support (SVM), régression logistique, Naïve Bayes et Random Forest. Ces algorithmes apprennent des données étiquetées pour reconnaître des modèles et faire des prédictions sur de nouvelles données invisibles. Les résultats montrent comment les modèles d'apprentissage automatique peuvent identifier et catégoriser les dysfonctionnements du travail d'équipe sur la base du modèle (lencioni,2015) de Lencioni. Pour chacun des cinq dysfonctionnements, des scores de précision moyens ont été calculés pour les niveaux faible, moyen et élevé. Les résultats montrent des difficultés à classer les cas modérés, dont la précision est souvent inférieure aux niveaux faibles et élevés pour tous les dysfonctionnements. Nous sommes raisonnablement convaincus que ChatGPT ou des technologies similaires fournissent une méthodologie viable pour générer l'ensemble de données souhaité, à condition que nous puissions améliorer la génération des dialogues et valider formellement la qualité de l'ensemble de données généré.

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I am immensely grateful to my father, to whom I promised to dedicate this dissertation before his death. My mother, husband, and children, in particular, deserve my gratitude. Their unwavering faith in my abilities has sustained my motivation and optimism throughout this challenging process.

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ACRONYMS

UQAM Université du Québec à Montréal.

SNCF Société Nationale des Chemins de Fer.

NOTATION

Nombres

a un scalaire.

A une matrice.

Unités

m un mètre.

W un Watt.

INTRODUCTION

0.1 Context

Social media have taken over a significant part of our daily lives. We can access all kinds of information through our smartphones, tablets, and other technological devices. Students dedicate a substantial amount of time engaging with social networking platforms such as Facebook, WhatsApp, TikTok, Twitter, Snapchat, Instagram, and others. Social media applications have become the most common methods of communication among university students (Shafique *et al.*, 2010; Hamat *et al.*, 2012; Legaree, 2015), most of whom have smartphones with internet capability, who spend a long time daily using them for connection, staying in touch, and increasingly for school work. Instant messaging applications have become the primary communication medium between students to share information about classes, ask technical questions, schedule meetings and work sessions, and, increasingly, collaborate on team projects.

The use of social media applications by students had been on the rise for a number of years, with each new generation of students, as social media permeated more and more of pop culture. Its effects on student academic performance and psychological well-being have been studied for a number of years, with conflicting results. Some studies have shown that social media facilitates learning, while others showed that it affects student well-being and results in frustration and self-harm (Abi-Jaoude *et al.*, 2020; Chukwuere, 2021).

Then the pandemic happened, and all learning switched online. Whereas prior to the pandemic students had the choice between different communication modalities and tools, with the pandemic, all learning and inter-student communications switched online to various messaging and communication applications. Concurrently, a number of professors, at UQAM and elsewhere, have noticed that the online switch coincided with an increase in team dysfunctions within the context of a 'team project' type of homework. This anecdotal evidence has been confirmed by more formal studies that reported similar trends (Onyema *et al.*, 2020; Wildman *et al.*, 2021).

This raised many questions, including that of the existence of a causal–or *contributing factor*–link between the *exclusive* reliance on social media to mediate teamwork and the exacerbation of team dysfunctions. The answer to this–and similar questions–may not be that simple because the measures put in place by public health authorities to mitigate the risks of COVID-19 propagation affected all aspects of our social and professional lives, with a marked, documented increase in mental health problems.

Given the pre-pandemic heavy reliance of Gen Z'ers on social media apps for all their social interactions, this raised the possibility that the problem does not come from the use of social media apps, per se, but instead comes from *inadequacy* of *social media apps* to mediate *team work*. However, again, the answer cannot be that simple. Large decentralized teams have been relying on electronic communications in the IT sector for decades. Thus, the hypothesis that electronic media are not suited for teamwork does not sound plausible, especially considering IT sector successes.

Interestingly, the literature on organizational theory has identified a range of teamwork modalities along the cooperation versus collaboration spectrum (Paulus, 2005), which require different interaction modalities, themselves requiring different communication bandwidths and channel 'richness'. This led us to explore the more refined hypothesis that ***the observed increase in team dysfunctions is due to the inadequacy of social media applications' communication functionalities to support (some?) teamwork modalities***.

0.2 Objectives of the thesis

0.2.1 Problem statement

The proposed research study is needed to design a model to identify group dysfunctions. Despite the widespread recognition of the importance of effective group dynamics, there remains a significant challenge in identifying and quantifying dysfunctions within team interactions, especially in real-time scenarios(Lencioni, 2012). Current methods primarily rely on subjective assessments or post-hoc analyses, which can be time-consuming and prone to biases. There is a need to develop such a model with some objective, scalable, and efficient approach that classifies and addresses these dysfunctions as they occur in real-time interpersonal dialogues.

0.2.2 A summary of research questions

The main research question is as follows:

> Does the increase in team dysfunctions, in the context of student team projects, come from the inadequacy of social media app communications functionalities to the kinds of teamwork modalities required by the projects done by the students?

Nowadays, team members communicate online to work and communicate, relying on applications like Zoom, WhatsApp, and MS Teams. This shift has led to team meetings being held online (virtually) rather than in person. Partners communicate through voice messages, video calls, or text conversations (dialogues). Some problems have been observed with virtual teamwork (Lam *et al.*, 2005). In this study, our primary focus is identifying the five dysfunctions in the dialogues. Specifically, we are focusing on a kind of analysis called "sentiment analysis." To do so, we want to train a machine learning model that learns about the five dysfunctions with the intensity level of each one. Since the research problem is identifying the five dysfunctions in text conversations between team members, we first need a dataset containing such exchanges with an associated label that includes manifestations of each dysfunction. The searches on such datasets proved unsuccessful. So, we had to build our dataset to be able to conduct our experiments, which became a research topic in itself.

This research study serves multiple purposes that can find utilization in real-time applications. However, the primary objective of this thesis is to develop a model that can accurately classify Lencioni's five dysfunctions in group dynamics through the analysis of interpersonal dialogues (Aggarwal, 2023). This research study has focused on identifying which groups have more ability to perform fruitful discussions in their group chats. This research study discusses the specific goals proposed below:

1. ChatGPT API utilization to generate a comprehensive dataset of interpersonal dialogues, ensuring a diverse and representative sample of group interactions.

2. Model development and training for accurately classifying and identifying the five dysfunctions in the dialogues.

3. Evaluate the developed model's performance and effectiveness in real-world settings and its applicability across various team environments.

4. Develop the model to get more training data to make it more robust and apply it to the diverse dataset for testing.

0.2.3 An overview of the methodology

To be able to answer these questions, we need to accomplish the following:

1. Develop a taxonomy of the different types of team projects and the different teamwork modalities that they require

2. Understand the different types of team dysfunctions to be able to, a) minimally, recognize them in team interactions, and b), ideally, trace them to their causes

3. Being able to map the communication functionalities of common social media apps to communication modalities identified in (1)

4. Design and conduct an experiment involving groups of students working on team projects, with the purpose of:

   (a) Characterize the type of team project using the taxonomy of (1)

   (b) Identify the tool being used, and map its functionalities using (3)

   (c) Analyze the trace of exchanges between the team members that were mediated by the tool to recognize, if applicable, the types of team dysfunctions that may have occurred

   (d) Interview the student team members for their own assessment of how the team work went

   (e) Correlate team dysfunctions, if any, to the combination of $<$project type, social media app functionalities $>$

0.2.4 An overview of the results

This study presents a new method to create a reliable labelled dataset by using ChatGPT APT. The methodology for generating dialogues using ChatGPT API is presented in section 5.3. After we had the labelled dataset, each dysfunction was trained with SVM, Logistic Regression, Naïve Bayes and Random Forest to prepare the trained model. These trained models were evaluated by the train_test_split technique used in Sections 6.4.2.1 and 6.4.2.2 yields reliable results when the test subset is selected randomly, which was the case. However, to get more reliable results, we use K-fold cross-validation, which uses (K) different breakdowns of the dataset between training and test data and averages the results. When dealing with a multi-class classification problem, the *stratified* K-fold cross-validation ensures that each of the K subsets is representative of the distribution of the classes in the full dataset. The results are shown in Section 6.4.2.3. The proposed model was able to classify the dysfunction accurately and get the evaluation measure values.

0.3 Contributions

The proposed model we have already mentioned aims to design a model that can deal with group dynamics in real-time group discussions. The following vital contributions to the field of group dynamics and computational linguistics are listed below:

1. The dataset is the backbone of the training, assessing, and expanding machine learning tasks. It plays an essential role in supervised model training; the model accuracy is based mainly on the data quality. The first step to train any supervised machine learning model is to obtain a well-labelled dataset. In our case, the labels we are looking for are the five dysfunctions with the three score levels(High, Medium, Low). After a comprehensive search of multiple dataset repositories, finding a dialogue dataset containing the five identified teamwork dysfunctions as potential labels was challenging. Therefore, there are two scenarios to overcome this problem. The first approach we take is to think of manual labelling, which is called annotation. However, data annotation is time-consuming and resource-intensive; it requires human annotators who may introduce subjective biases or inconsistencies, leading to probable inaccuracies in the labelled data, which leads to adding additional sophistica-

tion to the dataset preparation process(Paullada *et al.*, 2021). The second approach is to create a reliable labelled dataset from scratch by delving deeply into the five dysfunctions and carefully examining them to understand each individually. The proposed model in the thesis introduces a novel methodology for collecting and processing real-time dialogue data using the ChatGPT API, setting a precedent for future research in this area.

2. By utilizing the chat completion feature offered by ChatGPT API, the method we developed for generating dialogues comprises approximately 1000 dialogues with good results for creating a labelled dialogues dataset that addresses the five teamwork dysfunctions with their distinctive features that characterize each dysfunction from the other. This strategy provides an efficient way to create conversations that accurately capture the nuances connected to various levels of teamwork dysfunctions and offers a valuable tool for research and analysis in collaborative dynamics. This experimental exploration underscored the pivotal role of a well-annotated dataset in successfully training machine learning models, influencing their ability to make precise predictions and achieve reliable and effective model outcomes.

3. The model developed in this study represents a significant advancement in the application of machine learning within organizational psychology by creating a classification model based on Lencioni's dysfunctions. Additionally, the thesis presents a novel approach that offers empirical insights into the prevalence and characteristics of these dysfunctions across diverse group settings. This contribution enriches our understanding of team interactions and sheds light on the practical implications of addressing them.

4. It has offered practical tools and insights for organizations seeking to improve their team dynamics and overall performance by increasing the reliability of their operations.

0.4 An overview of the thesis

The remaining sections of the thesis are organised into several parts, each addressing a different aspect of the research. The following chapters of the parts are discussed below:

0.4.1 Literature Review

This chapter mainly focuses on defining what social media is, its types and features, the dark side of social media, the various communication technologies and previous studies on social media and examining several aspects, including applications and challenges posed for rethinking the concept of social media and its impact as a basis for communication and collaboration between people. Moreover, this chapter pays particular attention to the effects of using various social media sites in education. It highlights the enormous amount of text on social media, and no one imagines it is possible to look deeply into chat logs to discover a particular pattern or specific knowledge behind them, especially teamwork dysfunctions, which is the baseline of this study.

0.4.2 Methodology

In this chapter, we provided an overview of the research methodology employed in the thesis. It began with an overview of the research problem derived from our theoretical extension of the five teamwork dysfunctions. The extension led us to hypothesize that these five dysfunctions would emerge within team communication and produce distinct “signatures”. This hypothesis fueled our exploration of the communication needs and team dysfunctions, which resulted in developing a sentiment analysis model based on multiple machine learning classifiers to diagnose these dysfunctions within team communication. We explained how, through theoretical frameworks and empirical analysis combined with machine learning techniques, our systematic approach allows us to illuminate the subtle dynamics of teamwork to understand teamwork dysfunctions that hinder team success in organizational environments.

0.4.3 Characterizing Group Work

In this chapter, we explore and establish the essential concepts of group work. We will illustrate the different types and phases of group work and the differences and similarities between the several group work modalities. In particular, the literature has identified a "spectrum of modalities" of teamwork, ranging from pure collaboration, where several people work together on the same deliverable, exchanging points of view and reconciling differences, and cooperation, where significant work breaks down into relatively independent components, and each person (or subteam) works on one component of the whole. It connects what we already know about software projects in which the first phases (requirements, analysis, and design) are better done collaboratively to make the later phases cooperative: a good design is one where each subteam can work independently on a single component. Furthermore, the projects that require collaborative work vs. cooperative work necessitate different communication modalities, which social media tools do not necessarily support.

0.4.4 The Enron Data set as the basis for model training

This chapter illustrates an attempt to examine the dataset's problem: finding a labelled dataset for the five teamwork dysfunctions. We used the Enron dataset (Cohen, 2023), which consisted of email exchanges between Enron executives prior to the company's bankruptcy[1] To overcome the labelling problem, we propose using the 'Zero-shot classification' technique, which leverages pre-trained language models to label data automatically without explicit annotations.

0.4.5 Creating a Training Dataset with ChatGPT API

This chapter presents some of the creative scenarios for data collection. We use ChatGPT API to generate around 1000 dialogues distinct between team members and for all five dysfunctions, with three level scores(High, Medium, Low).

0.4.6 Model Training

This chapter explains the experimental design to identify team dysfunctions by detailing the preprocessing techniques employed and the development of the classification model using Machine Learning.

[1] The actual data set is available in: https://www.kaggle.com/datasets/wcukierski/enron-email-dataset

0.4.7 Conclusion

The final chapter summarizes the essential findings and contributions of the thesis and the directions for future research.

CHAPTER 1

LITERATURE REVIEW

1.1 Introduction

Social media have taken over a significant part of people's daily lives. We have access to all kinds of information through our smartphones, tablets, and other technological devices. Students dedicate a substantial amount of time engaging with social networking platforms such as Facebook, WhatsApp, TikTok, Twitter, Snapchat, Instagram, etc. Social media applications have become the most common method of communication among university students (Shafique *et al.*, 2010; Hamat *et al.*, 2012; Legaree, 2015). This includes students, most of whom have smartphones with internet capability, who spend a long time daily using them for connection, staying in touch, and increasingly for school work. This does not come without risk. The learners who are addicted to smartphones face constant interruptions from various applications on their devices while studying and lack sufficient self-control when it comes to adhering to their smartphone-based learning plan and its execution (Kibona et Mgaya, 2015).

The thesis vision stems from students' use of social media. The developing interest in social media further displays the extreme time spent using more than one application for conversation and work purposes. Students tend to favour social media systems over virtual learning environments, which include Moodle and Blackboard, for their conversation wishes. This long-time usage pursues a deep delve into numerous components of social media and its definition, attributes, and different types. Furthermore, it explores the ability drawbacks associated with immoderate social media use and its packages within instructional settings, particularly in facilitating institutional work. By inspecting exclusive modalities of group work amongst students, we additionally perceive capability challenges and dysfunctions that group participants may encounter, drawing insights from Lencioni's model on teamwork dysfunctions (Lencioni, 2012).

Social media use and abuse have been thoroughly studied in the literature. Some researchers focused on the influence of social media usage on students' educational achievements and the use of social media as an educational tool; others researched the benefits of using social media as a supportive communication tool for international students. Other studies looked at the impact of social media use on students' well-being and social media addiction. Reviewing previous literature reviews on social media is crucial for providing a theoretical framework, identifying research gaps, and evaluating methodologies. It will serve as the foundation for building an investigation into the relationship between social media communication functionalities and team dysfunctions in student-team projects.

1.2 Social Media

> "Social media are interactive technologies that allow the creation or sharing/exchange of information, ideas, interests, and other forms of expression via virtual communities and networks" (Kietzmann *et al.*, 2011; Obar et Wildman, 2015).

> The term "*Social media*" is "the application that allows users to converse and interact with each other, create, edit, and share new forms of textual, visual, and audio content, and categorize, label, and recommend existing structures of content" (Selwyn, 2012, p. 1).

> Social media is a virtual platform that allows people to make new connections, interchange knowledge, and refine people's relationships with each other. It refers to "a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of user-generated content" (Kaplan et Haenlein, 2010, p. 61).

Five user role categories were identified in the realm of Web 2.0, namely consumption, creation, sharing, facilitation, and communication (Slot et Frissen, 2007).

1.2.1 A brief history of social media

Social media's roots go much deeper than anyone can imagine. Despite its appearance as a recent trend, websites such as Facebook are the organic outcome of centuries of evolution in social media. People have used different methods to communicate from the very beginning. The history of social media began with the invention of the computer; it covers many eras to achieve its complete and evolving form.

1.2.1.1 Social media before 1900

The evolution of computers from the mechanical age to the electrical age was a great invention of humanity. The earliest method of long-distance communication was letters. People would write their thoughts and feelings on paper, and then send them to other people through a carrier. The earliest form of the postal service dates back to 550 BC. In 1791, Claude Chappe invented the semaphore communication method. The semaphore method was letting people communicate over long distances using two differently positioned flags representing letters of the alphabet or entire messages. It was used for many years, especially in France, to relay signals between ships at sea and when ships entered a port. In 1844, Samuel Morse used the electric telegraph, and telegraph messages were short, but they were a revolutionary way of conveying messages and information. Two other significant discoveries took place in the last decade of the 19th Century: the telephone and the radio in 1890 and1891 respectively (wikipedia, 2024)

1.2.1.2 Social media in the 20th Century

The 20th century witnessed rapid and significant transformations in technology. After developing the first supercomputer in the 1940s, scientists and engineers began building networks between computers. The ancient shapes of the Internet, such as CompuServe, was an American online service provider developed in the 1960s. During this time, engineers developed primitive forms of e-mail. Network technology had improved by the 1970s, and by the 1979s use, Net-enabled users to use a virtual newsletter for communication. In the 1980s, home computers became familiar, and social media shifted to be more complicated. The initial utilization of Internet relay chats (IRCs) dates back to 1988 and became famous well into the 1990s (Bechar-Israeli, 1995).

In 1997, another site called Six Degrees enabled users to create profiles, communicate with friends, and browse other user profiles. It alleges that “everybody in the world is linked to everybody else by no more than six degrees of separation”. Despite attracting millions of users, Six Degrees was unable to establish itself as a viable business and ultimately shut down in 2000 (Boyd et Ellison, 2007). In 1979 Jim Ellis and Tom Truscott conceived Usenet; at that period, Usenet, the extensively used Internet Discussion System, provides users with the ability to read and post messages within designated categories known as newsgroups (Taprial et Kanwar, 2012). In the late 1990s, another popular form of online posting, communication, and expression grew: the blog (an abbreviation of weblog). Blogs let users publish content such as blogs, photos, audio clips, and video clips. Initially, blogs began as static websites, but over time, they gradually evolved, incorporating numerous advanced features that significantly enhanced their interactivity.

1.2.1.3 Social media today

Social media has created ways to communicate and interact with others worldwide without being constrained by time and distance restrictions. After the blogging invention, the popularity of social media began to explode. Several social media sites have sprung up offering the features mentioned earlier and additional features like live video sharing and exchanging messages with diverse online groups can be observed across multiple online platforms and applications. During the early 2000s, platforms like Myspace and LinkedIn emerged as prominent players, while websites such as Photo Bucket and Flickr simplified the process of online photo sharing.

In 2004, a Harvard student, Mark Zuckerberg founded Facebook; however, it was reserved for Harvard students only when he launched the site. Following its initial launch, Facebook expanded its presence beyond Harvard University to encompass Stanford, Columbia, and Yale University within a month (Lee, 2014). Within a year, Facebook amassed a user base of nearly 1 million active users. Subsequently, the platform’s accessibility was extended to high school students and later to individuals aged 13 or older (Boyd et Ellison, 2007). As of September 2021, the average number of daily active Facebook users stands at a staggering 2.08 billion (statista, 2023).

In 2005, YouTube hit the market, opening up a new way to communicate and share over long distances. A vast number of individuals have the ability to discover, view, and distribute created videos. YouTube serves as a platform that enables people worldwide to connect, acquire knowledge, and inspire others, while also acting as a robust distribution channel for content creators and advertisers of all sizes. YouTube utilizes Adobe Flash Video technology to present an extensive array of user-generated video content, including movie clips, television clips, and music videos. Primarily, YouTube revolutionized the realm of social media by offering a user-friendly interface that simplified the process of uploading videos online, which was previously considered challenging, if not nearly impossible (Edosomwan *et al.*, 2011).

Twitter launched in 2006 and is a top-rated online microblogging service. It has a vast user base of several million users, known as followers. Each user sends periodic status updates, called tweets, which consist of short messages with a maximum of 140 characters. These updates can include personal information, messages, or links to pictures, videos, and articles. The posts made by a user are displayed on their profile page and their followers' timelines. (Asur et Huberman, 2010). Twitter has reduced the distance between people from different communities by enabling virtual face-to-face communication and discussion. This is because Twitter allows users to connect with others from all over the world, regardless of their physical location (Dewan et Ramaprasad, 2014).

1.2.2 Definitions and features (functionalities)

Although the terms social media and social network are often used interchangeably; they mean in fact different things. Social media is a communication channel, while communication in social networks is of a two-way nature. Essentially, social media serves as a platform for the distribution of information, while social networking is a platform for communicating. Several social networking sites started in the 1990s. Many people can communicate with niche social sites online, This includes public policy advocacy websites as well as a social network that operates on a network of contact forms and blogging services like Blogger and Six Degrees.

1.2.2.1 Web 2.0

Web 2.0 pertains to websites that prioritize user-generated content, user-friendly interfaces, and foster a culture of active engagement and participation, and compatibility with various products, systems, and devices for end-users. The emergence of Web 2.0 brought a wide array of tools that empowered individuals and businesses to construct, collaborate, share, connect, and engage with one another online. These Web 2.0 applications, also known as social media, are characterized by their intuitive nature, user-friendliness, social focus, adaptability, and a more informal approach compared to traditional information systems. (Kaplan et Haenlein, 2010) have categorized social media into six groups, which encompass collaborative projects (e.g., Wikipedia), blogs and microblogs (e.g., Twitter), content communities (e.g., YouTube), social networking sites/systems (e.g., Facebook), virtual game worlds (e.g., World of Warcraft), and virtual social worlds (e.g., Second Life) (Boughzala, 2016)

1.2.2.2 Honeycomb Framework of social media

Kietzmann et al introduced the social media honeycomb framework as a way to classify Social Networking Sites based on seven core functional components: Identity, Presence, Sharing, Relationships, Conversations, Reputation, and Groups (Kietzmann *et al.*, 2011, p. 243). Through their investigation of social media activities on the Internet, they observed a shift in consumer behavior from passive actions such as consuming content, reading, viewing, and making purchases or sales, towards more active engagement and participation. Multiple platforms have emerged, encompassing content-sharing sites, blogs, social networking sites, and wikis, that empower users to generate, modify, share, and engage in discussions about online content. Their research highlights the significant impact of the social media phenomenon on a company's reputation, sales, and even overall survival in today's business landscape. Despite the popularity of social media, many executives ignore it. The lack of comprehension regarding its functionalities, diverse manifestations, and effective utilization contributes to this situation.

Their framework shows the different social media activities and what they mean. Different social media may focus on one of several of these activities. Taking LinkedIn as an example, its primary emphasis lies in identity, reputation, and relationships. On the other hand, YouTube focuses on sharing, conversations, groups, and reputations. By examining the specific focus of each social media platform, users can gain a deeper understanding and effectively utilize them to maximize their benefits and advantages. This understanding allows individuals and businesses to strategically deploy the platforms in a manner that best aligns with their objectives, thus harnessing their full potential. The seven functional blocks of social media: (Kietzmann *et al.*, 2011)

- Identity: Identity encompasses the degree to which users disclose personal information within a social media setting, including details such as name, age, gender, occupation, location, and other consciously provided information (Kietzmann *et al.*, 2011).
- Presence: Presence indicates the spectrum of awareness through which users can determine the availability of other users. Additionally, it encompasses being aware of the whereabouts of others, both in the virtual and physical realms, as well as their availability for interaction (Kietzmann *et al.*, 2011).
- Sharing: Sharing represents whether, and how much, users exchange, share, and receive content (Kietzmann *et al.*, 2011).
- Relationships: The relationship aspect signifies the degree to which users can establish connections with other users. Establishing relationships implies that two or more users have some sort of association that facilitates chatting, sharing socialization items, arranging meetups, or mutually listing each other as friends or fans (Kietzmann *et al.*, 2011).
- Conversation Many, but not all, people primarily use social media sites to facilitate conversations between individuals and groups. The framework's conversation block represents whether, and how much users communicate with other users on social media (Kietzmann *et al.*, 2011).
- Reputation: Reputation relates to the range through which users can evaluate the status of themselves and others within a social media setting (Kietzmann *et al.*, 2011).
- Groups: The group function blocks exemplify the extent to which users can establish communities and sub-communities(Kietzmann *et al.*, 2011).

1.2.2.3 User-generated content

User-Generated Content (UGC), alternatively known as User-Created Content (UCC), encompasses a diverse array of content forms, such as text, images, audio, and videos, that users generate and share on online platforms such as social media and wikis. The video the user uploads to youtube, the photos he/she adds on Instagram, the Twitter post, the high score in online networking games, and the endless number of user-generated alternatives are all kinds of user-generated content (Obar et Wildman, 2015)

Various types of user-generated content exist, including internet forums where users engage in discussions on diverse topics, blogs that offer platforms for users to post about a wide range of subjects, and product reviews shared on vendor websites. Wikis, exemplified by Wikipedia, allow users, sometimes anonymously, to contribute and update content collaboratively. Additionally, social networks like Facebook, Twitter, and other social media platforms facilitate user communication through features such as chat functions, messaging systems, photo and link sharing, and content dissemination. Media hosting sites like YouTube enable users to upload and share their own content (wikipedia, 2024).

Looy et al have argued that three specifications should be satisfied before identifying content as user-generated, and they are:

1. Published, UGC needs to be published, In brief, openly available content (Van Looy *et al.*, 2016, p. 26).
2. Creative effort, UGC must be the result of inventive work. This element indicates that content should be created rather than just copying existing similar content (Van Looy *et al.*, 2016, p. 26).
3. Created outside of professional techniques and applications

> “The UGC should be outside of professional routines and practices. This excludes the connection between an organization and a business market to generate a

> payout. It also refers to (unpaid) users who produce content to network with like-minded people and become known as a specialist to show themselves" (Van Looy *et al.*, 2016, p. 26).

1.2.2.4 Mobile social media

Social media enables the establishment of online social networks by linking a user's profile with those of other individuals or groups. Smartphones are the driving force behind the modern age of social media. Cell phones (iPhones and tablets) or smartphones have already taken over all computer services. Presently, most social media sites are already combined with smartphones and mobile websites and specially designed mobile apps to serve all the networking demands of people. Portable social media enable people to chat and connect using their smartphones and other mobile devices. It empowers the creation and replacement of User Generated Content (UGC). UGC-based applications are growing more familiar to mobile users (Kaplan, 2012)

1.2.2.5 Social media Types

Most users are aware of social media sites and platforms, but they are not aware of their different functions, and they do not always make the best use of them. It is essential to clarify the different types of social media. Some types of social media are related to connecting with people (and brands) on the network. Other social media types are related to finding, and sharing pictures, videos, and other sorts of media.

Aichner and Jacob illustrated a typology of the types of social media as shown in table 1.1 (Aichner et Jacob, 2015, p. 259). It summarises the several types of social media with two famous examples for each category. Furthermore, Marketing and social media experts widely recognize that social media encompasses the following 13 categories or types:

1.2.2.5.1 Summary of social media types

Type	Name	Website
Blogs	The Huffington Post, Boing Boing	huffingtonpost.com boingbo-ing.net
Business networks	LinkedIn, XING	linkedin.com xing.com
Collaborative projects	Wikipedia, Mozilla	wikipedia.org mozilla.org
Enterprise social networks	Yammer, Socialcast	yammer.com socialcast.com
Forums	Gaia Online, IGN Boards	gaiaonline.com ign.com/boards
Microblogs	Twitter, Tumblr	Twitter.com Tumblr.com
Photo sharing	Flickr, Photobucket	Flickr.com Photobucket.com
Products/services review	Amazon, Elance	amazon.com elance.com
Social bookmarking	Delicious, Pinterest	delicious.com pinterest.com
Social gaming	World of Warcraft, Mafia Wars	warcarft.com mafiawars.com
Social networks	Facebook, Google+	facebook.com plus.google.com
Video sharing	YouTube, Vimeo	youtube.com vimeo.com
Virtual worlds	Second Life, Twinity	SecondLife.com Twinity.com

Table 1.1 Summary of social media types (Aichner et Jacob, 2015, p.259)

1.2.2.5.2 Description of social media types

1. Blog: A blog is a sequential arrangement of posts to let visitors read and comment on it. Both individuals and companies have the ability to publish news or other informative content on blogs, including product reviews (Aichner et Jacob, 2015).

2. Business networks: People employ business networks to establish and uphold professional connections, enabling registered users to develop personal profiles and share pertinent personal information, including educational background, work history, professional experience, and specialized skills. Companies, on the other hand, extensively leverage professional networks to enhance their employer brand and actively recruit new employees or specialists (Aichner et Jacob, 2015).

3. Collaborative projects: Collaborative projects collect Internet users with shared interests and specific knowledge to design, refine, recover, examine, and inquire about technological, educational, logical, or fun-oriented projects. Users can freely access all of the outcomes of these projects, such as applications, systems, and entertainment, quickly and free of charge (Aichner et Jacob, 2015).

4. Enterprise social networks: Corporate social networks are exclusively available to employees of a specific company or organization, providing functionalities akin to social networks, such as personal biographies and profile pictures. These networks enable corporations to ensure that their employees are acquainted with one another and foster the exchange of practices and concepts, ultimately strengthening the company's data and information management capabilities (Aichner et Jacob, 2015).

5. Forums: A forum serves as a virtual platform where users can pose questions to others, provide answers, and exchange thoughts, beliefs, or experiences. Unlike real-time chats, the interactions in a forum are time-shifted and visible to the public (Aichner et Jacob, 2015).

6. Microblogs: Microblogs gain popularity due to their limited post length, typically around 200 characters, which allows for quick and concise updates. This constraint often serves as a significant reason for their widespread adoption. Users can include various elements in their posts, such as pictures or web links. Additionally, users have the ability to subscribe to updates from other users, companies, brands, or celebrities, keeping them informed about the latest news and content (Aichner et Jacob, 2015).

7. Photo sharing: Photo-sharing platforms provide users with a range of services, including the ability to upload, host, manage, and share photos. These websites enable users to update their photos online, organize them into albums, and allow other users to leave comments on the photos (Aichner et Jacob, 2015).

8. Products/ services review: Product and service review websites offer information and insights about various products. These sites allow clients to both purchase products and access news related to them. Additionally, clients have the ability to rate products or specific

attributes such as product quality or drawbacks. They can also write or read evaluations and reviews provided by other users regarding the products (Aichner et Jacob, 2015).

9. Social Bookmarking: Social bookmarking entails the collection and organization of internet bookmarks on a centralized platform, with the aim of sharing them with friends and other users. These bookmarks serve as valuable references to public websites and other web content (Aichner et Jacob, 2015).

10. Social gaming: Social games refer to online games that involve and encourage social interaction among players. These games often require or provide opportunities for players to engage with one another, such as through multiplayer gameplay or card games (Aichner et Jacob, 2015).

11. Social networks: Social networks facilitate connections among individuals who are acquainted with each other, share similar interests, or desire to engage in related activities. Users maintain individual profiles, which other users can discover through their full names, and they can also upload photos and videos. Companies utilize social networks to create company profiles to promote specific brands, assist existing customers, and attract new customers (Aichner et Jacob, 2015).

12. Video sharing: Video-sharing platforms enable users to legally upload and distribute personal, commercial, or copyright-free videos. These websites typically offer features allowing users to comment on specific videos. Businesses leverage this form of social media to share advertisements, experiment with distinctive promotional videos, or reduce expenses associated with television advertising (Aichner et Jacob, 2015).

13. Virtual worlds: In virtual worlds, individuals have the ability to create their own unique avatars and engage in various activities, explore the virtual environment, and interact with other users simultaneously and independently. In contrast to computer games, the passage of time in virtual worlds continues uninterrupted even when the user is offline. These virtual environments often incorporate virtual currencies that possess real-world value, allowing businesses to sell both virtual and tangible products and services (Aichner et Jacob, 2015).

1.2.2.6 Viral Content

> "The term viral is the adjective of the noun virus (i.e., derived from Latin where the word refers to poison) but has been used for online content quickly becoming familiar" (Van Looy *et al.*, 2016, p.77)

Viral content is the content that everyone continuously receives. For example, any post, picture, video message, tweet, or any piece of information is considered viral content (yourdictionary, 2021).

Social media users can place the information they want to share with followers on their social networks, which will work virally as followers swiftly spread the original content to their followers, friends, and colleagues, such as reposting, resharing, and retweeting (Trusov *et al.*, 2010). Singh and Ishrat showed that influential users are the users whose level of activity has had a noticeable impact on the level of activity of others, as displayed by site logins over time, and accordingly, the overall volume of page views on the site (Singh et Singh, 2016). Surprising and inspiring content is highly likely to go viral. Users share content to tell others or improve their practical, helpful, and happy content. This type of content is often considered to be viral content (Berger et Milkman, 2012).

1.2.2.7 Bots

Bot, which is short for Robot, Social Bot, social media Bot, and Social Spam Bot, can be defined in multiple ways, and meanings change according to the research area.

> "It is a computer algorithm that automatically creates content and reacts with people on social media to simulate and possibly change their actions" (Ferrara *et al.*, 2016)

Other researchers defined bots as:

> " social media account software and no human user predominantly controls it" (Shu

et al., 2020)

There are many reasons for using bots. One could be political or marketing, like influencing opinions using various methods to search for specific social networks or conversations via an application programming interface (API) or influencing the topics in the chat of virtual users. These bots can have a bad reputation since they are used in misleading ways and are used as tools to disseminate fake news on the internet (Shu *et al.*, 2020).

1.2.3 Statistics on membership and usage

The Internet plays a significant role in multiple facets of our everyday lives, serving as an efficient, rapid, and cost-effective method of communication. It enables us to connect with a vast community within a short period and facilitates accessible communication with our family and friends. The reasons for using social media applications are many, such as keeping oneself informed about current news and events, researching brands and products, researching how to do things, education matters, study-related activity, gaming, meeting new people, and many more.

Statistics show that there are 4.66 billion internet users worldwide, which is about 60 percent of the world's population. With the outbreak of COVID-19, the actual figure may be considerably higher (Kemp, 2021). The average daily duration of mobile internet usage has surged from 32 minutes in 2011 to an estimated 155 minutes by 2021. Concurrently, the daily time spent on social media platforms rose from 96 minutes in 2012 to approximately 135 minutes in 2018 (Tandon *et al.*, 2020).

The Pandemic period affected people in many ways, including habits and daily routines such as watching TV and following the news. Social media platforms were used widely during the lockdown period, and they offered users opportunities to express their personal and group reactions to the pandemic outbreak. A recent study reported that many parents confirmed that their children's screen time had increased during the pandemic (Eyimaya et Irmak, 2021).

The interaction among social media users can be categorized into two directions: a positive direction aimed at coexisting with and overcoming crises, and a negative direction that seeks to exploit the crisis by spreading rumors, sometimes even promoting racist, criminal, or divergent ideological trends (Saud *et al.*, 2020) showed that social media platforms are convenient and accessible for anyone to share, post, and receive medical information about the COVID-19 pandemic.

1.3 The Dark Side of Social Media

Social media has connected people from around the world, enabling continuous communication regardless of geographical and time differences. With the widespread use of mobile phones, accessing the Internet has become effortless, allowing people to stay connected anytime and anywhere. Nowadays, mobile phones provide access to nearly all Internet applications, including voice and video calls, text messaging, video recording, and a wide range of engaging apps designed specifically for smaller screens. Overuse of social media apps leads to many adverse effects, psychological and social harm, and other problems caused by the overuse of these widespread platforms. If social media has a bright side, there are also dark sides, such as addictive behavior, Fear Of Missing Out (FOMO), cyberbullying, trolling, privacy abuse, fake news, and many others.

1.3.1 Social media addiction

The primary goal of technology and social media is to improve the quality of life and strengthen social relationships, but people's use of technology leads to the exact opposite. Social media carries enormous risk for individuals, communities, businesses, and even society at large. Some internet users cannot go to sleep before surfing social networks, and the first activity of the day is to pick up their smartphone to surf the internet again. Furthermore, excessive involvement with social media impacts adolescents' and students' sleep behavior, and they are at risk of developing an internet addiction. Internet addiction has many forms, and social media is one of them (Hou *et al.*, 2019; Tandon *et al.*, 2021).

The prevalence of social media platforms, coupled with the ease of internet access, has raised concerns about the potential for social media addiction and its impact on various aspects of daily life. Numerous studies have highlighted a correlation between the amount of time individuals spend on social media and the factors associated with addiction to these platforms. There exists a direct relationship between the duration individuals spend using social media and certain positive outcomes and the likelihood of exhibiting symptoms associated with social media addiction which reach the point where it interferes with other life tasks, leading to uncontrolled usage and more dire consequences (Ryan *et al.*, 2014; Al-Menayes, 2015).

Several studies have noted that unreasonable use of social media platforms distracts the brain, affects students' mental health, impairs their perception, causes mood and anxiety disorders, affects attention, and can develop into depression symptoms that correlate to mental morbidities (O'reilly *et al.*, 2018; Raudsepp, 2019). Moreover, there is a negative association between general social networking and student academic performance, and Facebook addiction is a severe and growing problem among college students (Tang *et al.*, 2016). If students do not manage these networks, they will become addicted and face various consequences, especially concerning their education. It is essential for higher education authorities to provide support for students who are dependent on social media networks and to conduct workshops that educate them about the adverse consequences of social media addiction (Azizi *et al.*, 2019)

1.3.2 Social comparison: Fear of Missing Out (FOMO)

The term "FOMO" is not new, it appeared years ago, and the first one to write about it was Dr. Dan Herman in the field of strategic marketing in 1996. Then the term spread widely with the tremendous technological progress and the rise of social networking sites. These sites have become sources of the latest developments, pieces of information, events, and local and international news (Rozgonjuk *et al.*, 2020).

Fear of Missing Out (FOMO) means to be afraid of missing out on other people's worthwhile experiences. Also, it was consistently a predictor of disruptions in the internet, smartphones, and social networks (Rozgonjuk *et al.*, 2020). This case is considered a behavioral addiction that separates us from reality to live in parallel in virtual reality.

Since the evolution of social media, the fear of missing out has become more apparent as these means have become platforms where human beings compare their daily life with the life events of other people, leading to a perversion of the concept of what is ordinary and natural. A person begins to feel that his/her accomplishments are inferior to others. A connection exists between the fear of missing out (FOMO) and academic performance among university students. Excessive and continuous smartphone usage can result in students becoming overly reliant on their devices, leading to a preoccupation with and exaggerated reactions to the actions and behavior of others (Qutishat et Sharour, 2019).

1.3.3 Cyberbullying

Bullying is behavior that often aims to emotionally or physically harm others. Cyberbullying is a type of bullying that uses the internet and related technologies to harm others deliberately. Cyberbullying is expanding day after day due to the extensive utilization of social media platforms and various mobile applications. Cyberbullying takes many forms, such as sending rude and offensive messages to one or more people, posting false messages about others, or excluding someone from an online group. Researchers have found that cyberbullying is more harmful than face-to-face bullying because cyberbullying messages or images last longer and keep hurting the victim (Faucher *et al.*, 2014).

Jackson et al (2014). conducted an online survey of cyberbullying behavior involving 1925 respondents at the university level. The primary forms of cyberbullying were (55%) social networks, (47%) email, (43%) text messaging, and (25%) non-academic-related blogs like forums or chat rooms. A contrast was discovered in the findings regarding cyberbullying, specifically in relation to gender. Female students were found to be more prevalent in reporting incidents of cyberbullying through social networks and text messages, while in non-academic-related blogs, forums, or chat rooms, male students exhibited a higher likelihood of reporting incidents of cyberbullying (Faucher *et al.*, 2014)

1.3.3.1 Cyberbullying and the Ability to Adapt to University

Bullying exerts its influence on various aspects of university life, encompassing both academic and social dimensions. Successful adaptation to university is crucial for achieving academic goals and maintaining psychological and social well-being during this sensitive phase of life. Although there are limited studies examining the specific correlation between cyberbullying and a student's ability to adapt to university, most research has concentrated on investigating the impact of cyberbullying on the university population as a whole. One previous study involved 1282 Spanish university students, who were analyzed to determine the predictive capacity of emotional problems such as anger, stress, and depression in relation to the ability to adapt to university in the context of cyberbullying. The findings revealed that higher levels of depression and anxiety increase the likelihood of becoming a victim of cyberbullying. Conversely, elevated levels of depression heighten the probability of engaging in cyberbullying behaviors. Furthermore, the student's personal, emotional, and social adjustments were found to decrease the likelihood of being a victim of cyberbullying (Martínez-Monteagudo *et al.*, 2020)

1.3.3.2 Cyberbullying and Academic Performance

University life is one of the most beautiful and most important stages that we go through in our lives, which has a significant imprint on the personality and thoughts of each individual. The concept of academic development encompasses not only educational experiences but also motivational factors and institutional commitment. Previous studies remarked that cyberbullying spread widely among students. It affects their academic performance adversely, degrades their academic scores, and some avoid attending certain classes or specific activities to escape bullies (Faryadi, 2011; Kowalski et Limber, 2013)

1.3.4 Trolling and fake news

The prevalence of social media has transformed it into a widely adopted platform for information retrieval and news consumption. The prevalence of social media has greatly facilitated the effortless generation and spreading of misinformation, encompassing rumors, spam, and fake news .

The extensive circulation of false information can have significant detrimental consequences on both individuals and society as a whole.

Misinformation refers to the dissemination of false or incorrect information, whether it is done knowingly or unknowingly. There are various terms closely associated with misinformation, including spam, rumors, and fake news. A closely related term is disinformation. The distinction between misinformation and disinformation lies in the intention behind their creation. Disinformation typically involves deliberate attempts to mislead, while misinformation often occurs unintentionally (Wu *et al.*, 2019).

On social media, college students occasionally engage in the sharing of misinformation, often driven by motives other than seeking accurate information. These motives may include sharing attention-grabbing messages or simply interacting with friends. The vast majority of students use social media platforms frequently, and sometimes they circulate news without knowing whether the shared content is misinformation or not. Therefore, students should be careful and responsible when sharing information on social media to avoid triggering suspicion and fear among individuals and groups. It would be worthwhile to help students reduce the exchange of misinformation (Tang *et al.*, 2016).

1.3.5 Privacy abuse

In the recent period, many social media platforms have spread, which have been exploited by many, especially the younger generation, to publish excerpts of videos and images of their daily activities using their smartphones. There is no doubt that each person has an aspect of his life, his time, and his diaries that he likes to share with his friends and those who are close to him, who feel comfortable with him, be it moments of joy or success, sadness, failure or other things. However, the matter is much more dangerous than a matter of entertainment. Some stalkers monitor many pages and accounts on social media, record details, and plan to commit criminal operations against them.

The widespread availability of social media, the longing to establish connections with friends, and the inherent need for validation are among the factors that drive users to frequently engage in posting content on the Internet. In most cases, users willingly reveal important personal information to keep their profiles as dynamic as possible. Many people may not be aware of their published results of such personal information in the virtual space open to the world, believing that they are doing an entertaining job that does not bring them any harm or problems (Turculeţ, 2014).

Previous research demonstrated that 84% of students agreed that sharing personal information on social media is risky, whereas 46% believed that social media did not keep data safe, so they did not want to share personal information on social media (Sharma *et al.*, 2015). Other researchers noted that students are not aware of protecting their data. Furthermore, Educational institutions are not actively raising college students' awareness, expanding their knowledge on social media privacy abuse, and protecting themselves from potential cyber-attacks such as identity theft, personal information leak, and hacking accounts and passwords (Moallem, 2019).

1.3.6 Political polarization

Before the Internet era, political conversations and thoughts were often conducted face to face within a closed frame and based on what newspapers and televisions broadcast. The widespread use of social networking sites shaped a new area for broadcasting events, news, and political opinions quickly and comprehensively for an endless number of sources and parties. In the context of the 2011 Arab Spring protests, social media networks played a pivotal role in the swift downfall of at least two regimes, namely Tunisia and Egypt . As an example, Facebook played a significant role in Egyptians' lives, including organizing demonstration calls and the youths' political parties and movements that came from it. At the same time, Facebook contributed to the sociopolitical mobilization in Bahrain and Syria.

Social media has seen many improvements and the development of tools that now use artificial intelligence techniques where feed algorithms are the basis for working on their platforms. They influence content promotion, consider users' preferences and attitudes, and affect political decision-making, and political communication, especially when it comes to polarizing topics. Undoubtedly, online users demonstrate a tendency to favor information that aligns with their existing worldview, disregard divergent information, and form polarized groups based on familiar narratives . In addition, incorrect information quickly increases with high polarization (Cinelli *et al.*, 2021).

Political polarization is a challenge that will affect society in the foreseeable future. Political polarization manifests in two distinct forms. The first is ideological polarization, characterized by the growing divide between political opponents in terms of their opinions, beliefs, and attitudes. The second form is affective polarization, which centers around political identity and the role of group identity in intensifying animosity towards those outside of one's own group (Kubin et von Sikorski, 2021).

Communications network facilitates the rapid and widespread dissemination of political information. Social media drives political polarization by creating "echo chambers" where individuals tend to primarily encounter opinions that align with their own or opinions of a similar nature. Social media can limit exposure to different perspectives and encourage groups of like-minded users who shape and reinforce a shared narrative. Previous research noted that Twitter users show higher levels of political activity. Using the Internet can also exacerbate mass political polarization, and social media contributes indirectly to polarization through increased political engagement (Conover *et al.*, 2012; Gruzd et Roy, 2014; Lee *et al.*, 2018).

The Internet has developed uniquely and speedily in recent years, and the computer and its applications have become vital in our daily lives. The use of computers and personal panels in the educational process has expanded, and opinions about the use of computers in education, in general, have varied between positive and negative. Most universities are now offering educational materials through the Internet and traditional methods. Adopting technology in education is abundant in features such as electronic books, periodicals, databases, encyclopedias, and educational websites. In addition, email allows people to communicate indirectly and asynchronously, eliminating the need for simultaneous presence or physical proximity, which is known as indirect communication. In contrast, direct communication provides the ability to communicate at the exact moment through written communication, audio and video communication, and video conferences, where the communication takes place live. Researchers in the field of the Internet and its communication relationship tried to rethink everything related to this bilateral communicative process and what are the role of the Internet and its applications in making communication successful in being more efficient and effective, especially in the university environment among students.

Computer-mediated communication (CMC) is clarified as communication mediated by connected computers between physically and temporally separated individuals or groups. Common attributes of computer-mediated communication (CMC) encompass the ability to engage in both asynchronous and synchronous communication, fostering high interactivity and enabling multipath communication. The first time CMC implementation was in the United States over a computer network named ARPANET provided a constrained multi-communication path connecting universities and government research institutes. Luppicini reviewed 170 research articles from 78 journals across all disciplines. The reviews encompass various areas of research in Computer-Mediated Communication (CMC) within the field of education. These include aspects that impact computer-based learning, such as media consistency and comparison, online courses and networks, course evaluations, group dynamics, peer evaluations, gender differences, implications for classroom practices, technology integration, teacher styles and characteristics, sociocultural factors, and the effects of professional development. Overall, research on CMC learning characteristics showed many positive results, including increased usability, easier interaction with trainers, positive learning experience, and performance benefits. Adverse aspects included immense workload, cost, deficiency of administrative provision, technological issues, and limited interactivity (Luppicini, 2007).

1.4 IT Technologies in Education

1.4.1 Overview

The use of technology has become pervasive in the 21st century. It supports learning and teaching and has undoubtedly changed the way we live (Raja et Nagasubramani, 2018). Classes are introduced through digital learning platforms to view courses and teaching materials anytime, anywhere. (Sarkar, 2012) and (Rabah, 2015) have argued that technology facilitates the learning process, which resulted in significant improvements in educational results, including student engagement. Other improvements include helping teachers with their lesson plans, facilitating personalized learning, and meeting global technological criteria. According to Desai (Desai, 2010), technology also helps refine the teacher's personality and open him to the outside world, expanding the student's knowledge efficiently. Moreover, it helps learners develop effective social skills, leading to effective learning (Lim, 2017).

Information technologies aim to make students more active in the learning process, develop the educational system, and improve education by using many different ways, such as communication technologies, content sharing, and collaborative work. Several studies have explored the extent to which new technology improves the language learning skills of learners (Carrió-Pastor et Skorczynska, 2015; Ahmadi et Reza, 2018). Elementary school and undergraduate or graduate students take advantage of the internet to learn about their assignments or do their research. Using social media, those who cannot communicate by email can instantly share information. For example, some professors use social media to notify their students of changes to their lecture schedule; on the other hand, students can express their opinions, expectations, or questions about course materials on a common platform (Büyükbaykal, 2015). Manca found that Facebook and WhatsApp are extensively accepted tools in higher education for various academic purposes (Manca, 2020). Former studies have shown that using social media greatly motivates students and enables positive learning experiences for teachers and university students (Awidi *et al.*, 2019; Durak, 2019).

The COVID-19 pandemic has affected the educational sector. It forced the closing of schools and colleges, leading to a sudden shift from face-to-face education to e-learning, requiring institutions that may have been resistant to previously using technology to adopt and utilize it on a daily basis and for several activities (Zalat *et al.*, 2021). A previous study examined the impact of COVID-19 on education among 200 respondents involving educators, students, parents, and policymakers selected from different countries. Their research results stressed the need and importance of introducing technology into education to manage the harmful effects of the coronavirus and other future pandemics in education (Onyema *et al.*, 2020).

1.4.2 Communication Technologies

The concept of e-learning emerged from technology and various digital learning environments. According to Abbad et. al, “e-learning is any learning made possible electronically by digital technologies or any learning that is web-based or internet-enabled" (Abbad *et al.*, 2009). E-learning takes place at different times, so the Internet and technology are needed to facilitate learning and communication. E-learning makes communication easier and improves the relationships that support learning (Zhao *et al.*, 2015).

> Communication is "the process of transmitting or sending a message" (Lim, 2017).

According to Lim, there are four components to communication: source, medium, receiver, and feedback (Lim, 2017). Lim distinguishes between synchronous and asynchronous communication. Asynchronous communication does not occur in real-time, and responses depend on the schedule of the sender or recipient; by contrast, synchronous communication takes place at a fixed time by using technology (Lim, 2017).

There are many advantages to using synchronous communication tools, such as facilitating real-time collaboration, immediate feedback, and no need for presence at schools or universities. The latter enables anyone to pursue an education from home. There are diverse communication technologies including email, social networking sites, video and web conferencing, and many others used for communication between students and professors. Most universities use social media groups and other freely accessible communication platforms such as ZOOM for scholarly communication (Sobaih *et al.*, 2020).

1. Email and Cloud storage

   Email is one of the earliest technologies used for electronic communication between teachers and students and between students in a university environment. It has found wide acceptance among students as an asynchronous communication tool necessary to facilitate interaction and learning (Uddin *et al.*, 2014). When students have questions about their tasks or homework, they can send them to their classmates or professors via email to receive quick answers and support each other in implementing and collaborating on their study projects.

Email facilitates asynchronous communication between students and teachers and is one of the patterns that support learning relationships even when they cannot be online at the same time (Khotimah, 2020). A previous study has reported that using email improves student learning levels, improves student-to-student-teacher interaction, and promotes aspects of lifelong learning for both students and teachers (Hassini, 2006).

Cloud storage has a significant impact on communication and collaboration among students, teachers, and workers. It is helpful for collaborative research through new peer reviews, social networks, and open access to information with links to real-time data. Cloud storage offers many advantages, such as saving lessons for uploading to the virtual classroom, and connecting teachers and students from everywhere. It reduces software and hardware maintenance costs and reduces energy consumption. It gives teachers the ability to share lesson files with students for editing and commenting (Thomas, 2011).

2. Forums

   Discussion forums are another example of asynchronous communication. Typically, the teacher posts a new discussion topic or concept; students can then start commenting on it and sharing their views on it. There are many advantages of using a discussion forum, such as motivating students to read more about a specific concept, encouraging brainstorming, and providing feedback; these result in successful communication and innovative thinking skills, and contribute to collaborative learning. Assessment feedback performed using online discussion platforms is an integral part of effective teaching and learning and can be one of the most effective approaches to improving and increasing student learning. Feedback posted online gives students the flexibility to read it at their own pace and focus more on the comments without their peers (Sadler, 2010). Previous research has shown that asynchronous discussion boards can be a powerful tool for reflecting on each learner's level of cognitive engagement in the learning process. In addition, individual student contributions to online discussions at specific attendance groups are beneficial predictors of student academic performance (Galikyan et Admiraal, 2019).

3. Content sharing:/ adopting social web

   Students make heavy use of social media sites, and there is a general impression that students are wasting a lot of time. However, there could be advantages to using social media wisely and carefully. Social media platforms have revolutionized the conventional classroom by creating an interactive environment that fosters student engagement, collaborative learning, and reflective thinking. Presently, the utilization of social media in educational institutions, including universities, schools, and various learning establishments, has witnessed a surge. This is primarily attributed to the active role played by social media in facilitating communication among diverse communities. These platforms have equipped learners with a multitude of tools that enable them to effectively communicate their ideas and opinions, as well as facilitate the exchange and sharing of knowledge. Previous researchers have examined students' experiences of using social media sites to raise awareness among university teachers of the need to move from formal to informal learning. The study results showed that social media sites such as Facebook, WhatsApp, Pinterest, YouTube, Wikis, and others sustain participatory and active learning among university students. Therefore, further research into this area may be helpful for the acceptance of Social Media Sites for interactive learning driven by social and personal experiences to acquire knowledge (Mpungose, 2020). Another previous study conducted on 308 university students from Saudi Arabia implied that the use of Social Networking Sites for chats and discussions and file sharing among university students every day has a positive effect on their knowledge-sharing and learning (Eid et Al-Jabri, 2016).

1.4.3 Collaborative work

Collaborative or cooperative learning looks to have the same meaning. Pateşan et al have distinguished the difference between them. They defined collaborative learning as a way of teaching and learning in which students work in groups to conduct research on an important topic or to perform a meaningful project. At the same time, cooperative learning is a special type of collaborative learning in which students work in small groups on an organized project. When students work in small groups, they tend to acquire a deeper understanding of the subjects being studied and retain the information for an extended period. Simultaneously, this collaborative approach to learning often results in higher levels of student satisfaction with their lessons since they are receiving knowledge from their peers and tutors jointly (Pateşan *et al.*, 2016). Al-Rahmi et al noted that information sharing, learning activities, knowledge sharing, and discussions with peers are essential factors that improve collaborative learning through social media. Future studies should consider other factors that affect Internet interaction, such as smartphone activity, to enable interactive learning environments between students and their teachers (Al-Rahmi *et al.*, 2018).

1.5 Social media in education

1.5.1 Introduction

The world we live in is vast, and it is not easy to reach people from different areas. Nevertheless, technology makes collaboration and exchange possible by connecting people from various areas and places and meeting in a virtual space to exchange diverse views and skills. Modern technology plays a significant role in the education process, which is essential in shaping the new educators' success to become a tool in bridging the gap between nations. Digital communication and collaboration skills allow learners and educators to interact effectively, elaborate on ideas, and learn from each other. There are many reasons why university students use social media apps heavily. Smartphones are powerful enough to function as a laptop or desktop computer, allowing students to easily see, share, post content, and chat with one another. Some students may prefer to express their feelings on social media; others can use it for commercial purposes, e.g., to gain followers and earn money. Others interact with their friends and share life activities on social media. Expatriated students may feel more secure and comfortable talking and chatting with family members and friends via social media apps.

High school and college students have started to benefit from social networking sites. Social media helps them establish their social community. Students prefer to connect and chat using social media instead of official platforms like learning management systems and academic portals. There are exciting features, attributes, and details that should be explored in social media apps to know why they prefer using social media more than other formal platforms. The endorsement of using social networking sites has increased, and this is due to the existence of many social networking sites. Social media like Facebook have a positive effect on students. Students can achieve full knowledge and helpful information, improve their academic performance and study excellence, and deepen essential concepts such as collaborative education and e-Learning. Although it has many positives, the negatives outweigh the positives. Students are prone to setbacks, as it distracts them from studying when they use it for non-academic purposes.

Various researchers have researched to determine the impact of social media on users. Morallo researched 203 students at six colleges in the Lyceum in the Philippines. The study showed a significantly positive association between time spent on social media and their academic performance. The use of social media shortened the students' study time and extended their free time. Students mainly used social media for non-academic purposes, entertainment activities, and communicating with friends. It is important to highlight the use of social media in the learning process, mainly activating social learning, which means delivering learning through social media in higher educational institutions to guide students to use their online time wisely (Morallo, 2014).

As mentioned earlier, information technologies aim to make students more active in the learning process, develop the educational system, and improve education in various ways. Social media has the power to serve the education sector in a positive and beneficial way. There are many different approaches to using social media for education. It is essential to understand social media's impact on education before using it.

1.5.2 Impact of Social Media Use in Education

Technophobia is a barrier to implementing ICT in education for many reasons. In the past decades, the teachers' job was mainly to transfer information to the learners' minds, with complete adherence to the topics stipulated in the curriculum and the information contained in the approved textbooks. The teacher was concerned with this mastery more than the value of the information for the learner. This led the teacher to encourage competition among learners in studying the prescribed subjects instead of training them to cooperate to reach common goals and learn from each other. Some educators are not convinced by modern methods. They struggle to avoid using technology in their classrooms and stick to traditional learning methods. At the same time, some fear that technology in education could endanger their professional future, as they may be seen as less valuable if they are not using the latest technology. Additionally, some educators lack the qualified skills in handling technological resources, and there is a lack of adequate financial support to build a technological infrastructure suitable for using technology in education.

One of the concerns shared by educators and academics is examining and understanding social media's potential importance and likely impact on educational practice and offerings, especially in higher education settings. Several studies have examined the impact of social media on student lives, academic performance, habits, life routines, and many other aspects. The attitudes of teachers influence the use of social media. Teachers' mastery of social media is critical to motivating students and making social media an educational background rather than wasting time chatting, watching, and sharing videos. Teachers should effectively integrate learning tools with pre-established learning objectives to ensure a coherent and meaningful learning experience. Educators need to be attentive to the potential distractions that can arise from the use of Facebook in the classroom and provide appropriate guidance to students (Niu, 2019).

Unquestionably Facebook, being a highly popular and extensively utilized social networking platform, plays a significant role in e-learning. It enhances the educational process by offering a range of applications that enable teachers to incorporate exercises and showcase content to enrich the learning experience. Facebook offers a free option that can be used effectively in education. Facebook groups, which post lessons and academic units, allow the creation and distribution of content in multiple images and formats and provide tools and options for managing groups. This social learning function was introduced on April 30, 2019. It enables any group administrator to format the content in structured units to create courses and share them with members (elearningindustry, 2021).

Integrating Facebook into the education sector has many advantages and benefits, such as interaction, connectivity, collaboration, and increased student engagement. Many authors have researched the effects of using various social media sites in education and they found the following advantages/benefits:

1. Social Media increases communication between students and teachers and students and facilitates group discussions (Willems et Bateman, 2011; Dunn, 2013; Boateng et Amankwaa, 2016; Gunawan *et al.*, 2018; Giannikas, 2020).
2. Social Media fosters collaborative learning between students and peers (Willems et Bateman, 2011; Dunn, 2013; Ansari et Khan, 2020; Giannikas, 2020).
3. Social Media allows students to study course materials outside of regular class hours(Willems et Bateman, 2011; Dunn, 2013).
4. Hovorka and Rees found that incorporating social media into courses makes them more exciting and fun and teaches students valuable and pervasive skills in the workplace, such as communication, collaboration, community, closeness, and creativity (Hovorka et Rees, 2009). Friedman named them the 5 C's, the characteristics of social media(Friedman et Friedman, 2008).
5. Social Media provides an alternative to institutional learning management systems and deals with technologies and skills to promote student employability (Willems et Bateman, 2011; Dunn, 2013).
6. Chawinga stated that social media like Twitter and blogs make students more enthusiastic about learning and positively affect students' scores (Chawinga, 2017).
7. Niu reviewed several empirical studies about using Facebook for academic purposes, and 57 of them demonstrated the following results:
   - There is a notable enthusiasm for incorporating Facebook into formal teaching and learning endeavors.
   - Facebook serves as a valuable platform for enhancing communication, fostering collaboration, and facilitating the sharing of information in the realm of learning(Niu, 2019).

- Using Facebook as a learning platform has promoted student-centered learning. Future research could explore the impacts of using social media on students' satisfaction levels or instructor ratings(Niu, 2019).
- The implementation of Facebook as a replacement for LMS has not yet been adequately researched. Future research endeavors should aim to delve deeper into the exploration of whether and how Facebook can be effectively utilized as a LMS (Learning Management System) and how an appropriate balance between academic and social use of Facebook could be achieved(Niu, 2019).
- The incorporation of Facebook into learning endeavors should be aligned with the specific learning context, materials, and objectives of a given course. For instance, when the course content necessitates active learning, Facebook may be utilized as an auxiliary tool. Ensuring a harmonious match between Facebook's capabilities and the learning objectives and content of the course can be crucial for its successful integration(Niu, 2019).

8. In a two-year longitudinal study conducted by Nalbone et al involving 1,033 students in the United States, it was discovered that Facebook facilitates increased interaction between students and faculty members. Furthermore, the study revealed that students who utilize Facebook during their studies demonstrate enhanced adaptability to the academic environment and exhibit higher retention rates (Nalbone *et al.*, 2016).

9. Mostafa, 2021 showed that using social media for professional learning is desirable for teachers working in rural and remote areas. Teachers expressed interest in collaborating through social media to overcome isolation. Social media can offer them opportunities to communicate with each other, collaborate and support each other synchronously and asynchronously(Mostafa, 2021).

1.5.3 Group Work in Education

1.5.3.1 Overview

The collaborative nature of group work creates an ideal environment where student interaction takes center stage in the learning process. The ability to work in a team is important as it is the key to success in most areas of life and work. Looking closely at group interaction in online learning environments is necessary to foster effective interaction. Definitions of the word group are varied as groups themselves. A common feature of many of these definitions emphasizes social relationships that bind members together. When three individuals work on math problems in separate rooms without any form of connection, it can be challenging to consider them as a group. However, suppose we establish relationships between them, such as enabling the exchange of notes or designating one person to distribute the problems to others. In that case, these three individuals can be seen as forming a basic or rudimentary group (Forsyth, 2021).

The Corona Pandemic caused an apparent change in the education sector by moving from a face-to-face learning system to distance learning, leading to a change in the mechanism for practicing classroom activities electronically and in groups within the virtual environment. During the pandemic, the role of social media for educational purposes has gained prominence as it improves connectivity and provides opportunities for collaboration. It has become substantial in all society segments; its adoption has become an urgent necessity. After schools and universities became students' second homes, social media became the platform for students to express their opinions and ideas. For example, the "Zoom" app makes it easy to communicate between teachers and students by downloading to mobile devices. Using synchronous applications with supporting features facilitates the exchange of ideas and information and leads to progress in learning and work. This sudden shift severely impacts stress, well-being, and happiness for people trying to accomplish their goals online. Most of the research conducted thus far has primarily concentrated on the individual effects of the pandemic, specifically regarding work productivity and mental well-being (Luchetti *et al.*, 2020).

1.5.3.2 Conflicts in group work

> Conflict is "the process by which people or groups perceive that others have taken actions that harm their interests" (Levi et Askay, 2020).

Conflict occurs in group work, but the most formidable challenge when it comes to conflicts is transforming them into constructive experiences rather than merely enduring them in group work. Harmony and appreciation should coexist in a classroom setting, and conflict should not negatively impact learning activities. Flexibility and convenience allow students to connect with group members anywhere, anytime.; social media applications and email allow students to communicate with each other at any time. Teamwork is a challenge in itself. Some significant obstacles can make this type of work difficult. Problems often arise with online group work as some students' Internet connection is not as stable as others, which hinders communication between group members. Another weakness is communication difficulties. For example, some students worry about communication problems they might encounter since they cannot see each other face to face.

Conflicts are commonplace in our lives; everyone has to experience them at some point. However, sometimes they are necessary and valuable in the group work environment; Because it involves brainstorming and exchanging views, which is beneficial in moving the work forward and making the necessary changes, but can also have negative effects. Conflict can come in all forms and many types. Conflicts have positive and negative consequences. Finding ways to manage and deal with them is very crucial. Table 1.2 distinguishes the different shapes between healthy and unhealthy conflicts.

Unhealthy Conflict	Healthy Conflict
An inability to listen to each other.	Ability to listen to each other and express disagreements.
Unhealthy reactions such as hurtful words, negative statements, and offended reactions.	Express ideas without being bullied or belittled for having different opinions.
Disrespect disagreements.	Differences esteem.
The dominance of the authoritarian's opinion and the failure to achieve the desired goal.	Reach specific, intended goals.

Table 1.2 The differences between healthy and unhealthy conflict

Lencioni presented a dynamic model consisting of five dysfunctions, showcasing how teams fail to effectively collaborate. These dysfunctions include: 1) absence of trust, 2) fear of conflict, 3) lack of commitment, 4) avoidance of accountability, and 5) inattention to outcomes. By recognizing these underlying causes of ineffective teamwork, Lencioni suggested that teams can implement targeted approaches to address each dysfunction. This would result in increased comfort levels, active participation in constructive discussions, clear alignment and agreement on team objectives, adherence to high standards, and a collective focus on team outcomes rather than individual aspirations (Lencioni, 2012).

Wildman et al. conducted research on student teamwork during Covid19. The examination of 90 open-ended survey responses in the study presented an opportunity for students to collaborate in project teams during the pandemic to express their experiences. The findings of the study unveiled that the challenges faced by these students encompassed alterations in team communication, tasks, roles, as well as the repercussions on team progress and outcomes, as illustrated in figure 1.1 (Wildman *et al.*, 2021)

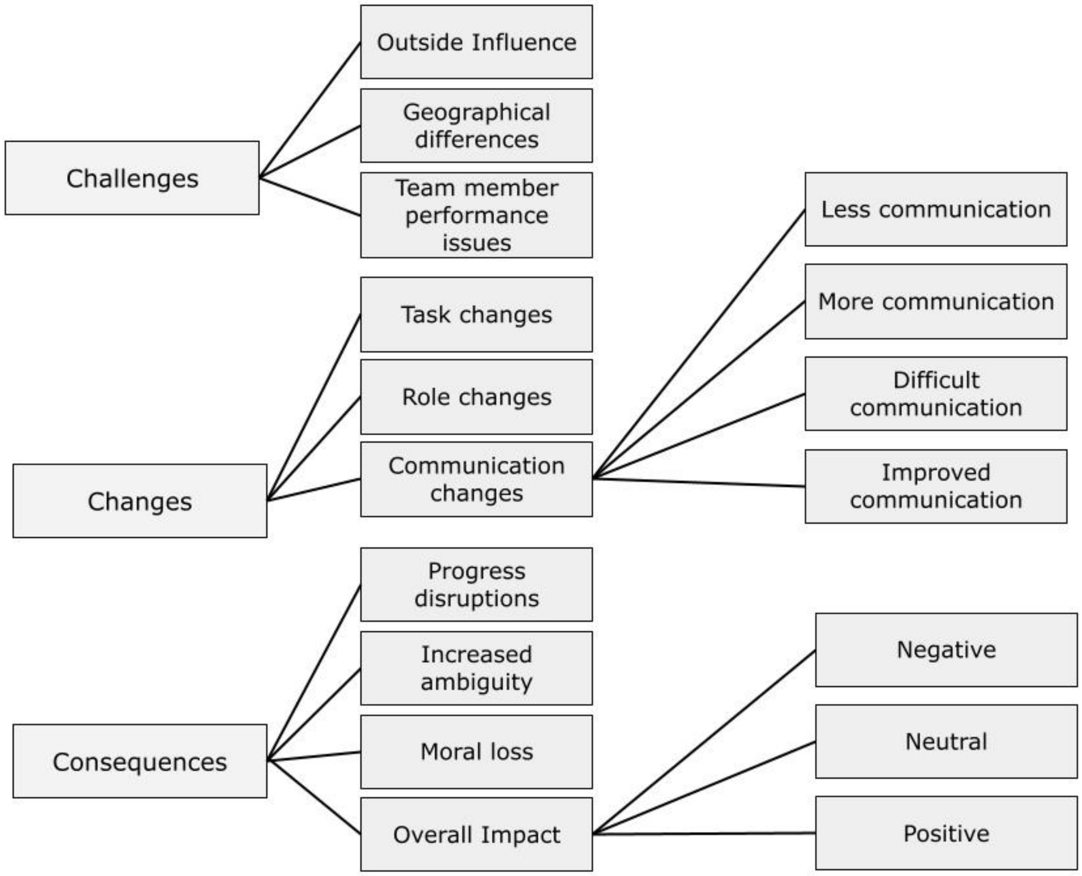

Figure 1.1 Challenges, changes, and consequences for student teamwork during COVID-19 (Wildman *et al.*, 2021)

1.5.3.3 Collaboration vs Cooperation

Cooperative and collaborative learning are ubiquitous, especially in group activities. Cooperative learning is a group-structured learning method in which students are divided into small groups and assigned specific roles and tasks by the teacher. In collaborative learning, the students agree on the effort among themselves. Correct collaboration is valuable; it allows students to learn from each other, negotiate and advance their academic, communication, and social skills. The collaboration aims to create new insights in discussions and to bring the students closer to understanding alternative perspectives. When evaluating whether a classroom task is genuinely collaborative, it is crucial to consider certain key aspects. These include the students' ability to negotiate and accommodate each other's perspectives, as well as ensuring that everyone contributes equally to incorporate diverse viewpoints into the final work (Kozar, 2010). Paulus researched to examine collaborative versus cooperative tasks in an online environment. The study revealed that groups tend to cooperate more than collaborate in group tasks (Paulus, 2005)

Previous studies of social media use in education have focused on specific uses of social media, such as collaborative learning and communication among peers. Many researchers have discussed using social networking sites as learning tools. These studies have shown that social networking sites' main benefits are communication, collaboration, and motivation. However, social networking sites have two characteristics that influence learning development in students and academics and have not yet been explored: synchronous and asynchronous capabilities. An example of synchronous communication is video communication and online classes, in which students and professors can meet online, discuss, and at the same time work together regardless of location. The second key feature of social media is its asynchronous role, allowing teachers and students to send, receive, interact, and collaborate independently of time and place. Giannikas suggests that future research should examine different functions and uses in social media to differentiate their unique uses in the university context (Giannikas, 2020), whereas Khan et al. recommended that future research be conducted with teachers to comprehend their perspectives on the acceptance of social media for collaborative learning (Khan *et al.*, 2021).

1.6 Social Networking Analysis

In one day, one person conducts many correspondences, whether via e-mail or SMS; the vast majority are through text messages through social media and its various applications. There is an enormous amount of text on social media, and no one imagines it is possible to look deeply into chat logs to discover a particular pattern or specific knowledge behind them. Social network analysis represents a specific social network or circle. It studies the relationships between users and influencers, the types and forms of data disseminated in each relationship, and the types of communication between them that are known to users. Data analysis is used widely in social media analysis, especially in determining its dynamics and exploring the patterns (Irfan *et al.*, 2015). Analyzing team communications, and more specifically, using natural language processing (NLP) and machine learning techniques, have proven very effective at *sentiment analysis* (Taboada, 2016). Sentiment analysis techniques are introduced in Section 2.5 and a more detailed for sentiment analysis is presented in chap 6.1

1.7 Conclusion

In this chapter, we present a brief history of social media, define what social media means and what social media networks mean, two terms for different meanings 1.2.2, we show the several types of social media and we provide the negative effects of social media 1.3. In addition, this chapter introduces some of the findings of previous work in using social media in the academic context listed in section 1.5.2. Previous research recommends examining different functions and uses in social media to differentiate their unique uses in the university context and conducting research with teachers to comprehend their perspectives on accepting social media for collaborative learning (Giannikas, 2020; Khan *et al.*, 2021; Wildman *et al.*, 2021) with the sudden shift from Face-to-face to online learning and the students' use of many social media tools to perform team projects and assignments. We organised our methodology framework based on the team dysfunction diagnostic tool developed by Lencioni (Lencioni, 2012), which relies heavily on what team members say/write. In the following chapter, we transition from the foundational literature review furnished right here to a deeper examination of our methodology framework 2.

CHAPTER 2
METHODOLOGY

In this chapter, we present the research methodology that guided our work during the thesis. We start with an overview of the research problem and how we set out to address it in this thesis.

2.1 Problem statement: a refresher

Social media applications have become ubiquitous in our daily lives. They are used intensively by most age groups, but their use is nowhere as pervasive as it is with Gen'Zers who use them to mediate interactions with family members, friends, and schoolmates. At the outset of the pandemic, all learning turned virtual, and social media apps became the *only* way students communicate with their peers to exchange information about classes, ask technical questions, schedule meetings and work sessions, and collaborate on team projects. A number of academics have observed that the online switch coincided with an increase in team dysfunctions within the context of 'team project' type of homework (Onyema *et al.*, 2020; Wildman *et al.*, 2021).

As explained in previous chapters, the problem could *not* have come the gen'Zers resistance to social media apps as communication media. It could not have come, either, from the blanket inadequacy of virtual communication for teamwork, as decentralized teams in many fields–most notably IT–have been successful with virtual communication. This led us to the more refined hypothesis:

> Does the increase in team dysfunctions, in the context of student team projects, come from the inadequacy of social media app communications functionalities to the kinds of teamwork modalities required by the projects done by the students?

In this chapter, we present the research methodology that we set out to implement to answer this question. As we explain in later sections of this chapter and subsequent chapters, the actual implementation of this research methodology led us to explore other, but no less challenging, problems.

We first start by presenting the overall methodology 2.2, and then present the steps of the methodology in the different sections.

2.2 Overview

To test whether the observed increase in student team dysfunctions is due to the inadequacy of social media applications communication functionalities for teamwork, we need to do the following:

- (O_1) Determine what the communication needs for team projects are,
- (O_2) Validate whether the absence of social media app functionalities that meet those needs can be 'linked' to team dysfunctions.

With regard to the first item, we mentioned earlier that past and documented successes of virtual teams prevent us from making blanket statements of the kind "social media apps cannot support teamwork", because of the diversity of electronic communication tools–social media apps being one subcategory–and the diversity of project types. Accordingly, this step will involve three sub-steps:

- ($O_{1.1}$) Adopt, or develop a classification of team-group work styles,
- ($O_{1.2}$) Identify the types of projects that require the different group work styles, and
- ($O_{1.3}$) Establish, for each group work style, the communication needs between the various stakeholders.

This is done in chapter 3, where we build on the literature in organizational theory to propose a classification of group work styles along the *cooperation* versus *collaboration* spectrum. The three sub-steps are summarized in section 2.3.

The fact that some project types have specific communication needs that are not met by communication tools does not imply that the affected work teams are dysfunctional. Generally speaking, the inadequacy of tools used by teams does not result into dysfunctional teams. They may lead to slowed down, or frustrated teams. Most IT teams have some tool, framework or language to gripe about. Thus, the first sub-objective of (O_2) is:

- ($O_{2.1}$) Characterize precisely what is meant by *team dysfunction*. We may have an intuitive understanding of what team dysfunction is, but we need a precise operational definition that can help support scientific experiments.

Having precisely characterized team dysfunction, we can pursue objective O_2 *empirically* as follows: given a set of past team projects, for which communication history and team members are available, do the following for each project P_i:

1. ($O_{2.2}$) Categorize the project along the classifications produced by ($O_{1.1}$) and ($O_{1.2}$);
2. ($O_{2.3}$) Assess whether the project team exhibited one or more of the types of dysfunctions identified in $O_{2.1}$;
3. ($O_{2.4}$) Identify the tools used by the team for communication, and assess the extent to which the tools used support the type of communication or coordination required by the project category, as characterized in ($O_{2.2}$); and
4. ($O_{2.5}$) Establish the nature of the relationship, if any (correlation, precedence, causality, etc.), between functionality mismatch, if any ($O_{2.4}$), and team dysfunction, if any ($O_{2.3}$).

Within an academic context, we expect the categorization of projects or work styles (objective ($O_{2.2}$)) to be relatively easy, as team projects typically have a built-in learning objective of practicing a *team work style*, that is often explicitly stated in the project assignment description.

We expected more challenges regarding objective ($O_{2.3}$), i.e. assessing whether a past project team exhibited one or more signs of team dysfunctions. This depends on two factors:

- What aspects of team operation are affected by the documented dysfunctions. For example, dysfunctional teams have under par productivity levels, deliver products of low quality, may have high turnover, etc.
- Which of those aspects are easily observable and *can* be attributed *solely* to the dysfunction at hand. For example, low quality can result from many ills, including inadequate tooling, incompetent priority management,

As it turns out, team dysfunctions are easily recognizable in team communications. A keen observer can attend a team meeting and quickly diagnose team dysfunctions. The team dysfunction diagnostic tool developed by Lencioni relies heavily on the utterances of team members. Anecdotally, my research advisors, with a combined 50 years of teaching experience, have often been taken as witnesses by unhappy student team members, showing electronic exchanges to show how their teammates are not behaving appropriately.

Accordingly, we decided to identify team dysfunctions ($O_{2.3}$) by analyzing team communications, and more specifically, to use natural language processing (NLP) and machine learning techniques to analyze team communications to identify team dysfunctions. These techniques, used in combination, have proven very effective at *sentiment analysis* (Taboada, 2016). Sentiment analysis techniques are introduced in Section 2.5.

The identification of team dysfunctions can be thought of as a supervised classification. To this end, we need to do the following:

- ($O_{2.3.1}$) Identify those *features* of team communications traces that are indicative of the various dysfunctions;
- ($O_{2.3.2}$) Acquire or develop a labeled dataset of team communication traces with properly identified team dysfunctions;
- ($O_{2.3.3}$) Use the labeled dataset to train a machine learning model to recognize those features in team communication traces;

- ($O_{2.3.4}$) Use the trained model to detect instances of these dysfunctions in team communication traces.

Using sentiment analysis techniques to recognize team dysfunctions is summarized in Section 2.6. As it turned out, the acquisition of the labeled dataset ($O_{2.3.2}$) was a *major problem*; it is presented in a Section 2.7. We conclude this chapter in Section 2.8.

2.3 Characterizing Group Work Communication Needs (O_1)

Group work frequently manifests in our daily lives, such as in the workplace, educational settings, and social contexts. A thorough understanding of group work methods can significantly contribute to accomplishing shared objectives (Wilson *et al.*,). Different styles of group work emerge, each with specific characteristics, including their communication needs. We start by identifying group *work styles*, and then discuss the communication needs for each work style.

The primary two modalities of group work are *cooperation* and *collaboration*, with many styles in between. Individuals sometimes practice one or both with distinct meanings without recognising the nuanced differences, depending on the type of project or task and communication needs. Cooperation entails individuals working independently without exchanging knowledge. Tasks are divided, with each team member responsible for completing their assigned part. on the other hand, collaboration endeavours having everyone sharing and exchanging knowledge to innovate and create collective goals. All team members work together synergistically to achieve group goals rather than individual ones. Both methods have their benefits in varying circumstances. Within an academic context, students typically engage in both cooperative and collaborative efforts. Occasionally, students cooperate to complete their parts and subsequently collaborate to submit the whole project collectively. The combination of collaboration and cooperation facilitates the acquisition of competencies for independent assignments and collective endeavours.

Cooperative group work comes in two flavors: formal and informal. Within the context of *learning*, the distinction between formal and informal cooperative learning lies in the duration, size, and level of involvement, each serving specific functions within the educational setting. In formal cooperatives, group work is formed for an extended period, and the teacher is responsible for defining the work objectives, assigning roles to the students during discussions, and evaluating the work performance. With *informal cooperative learning*, groups are formed for a limited time and are smaller; students might cooperate to perform tasks for one lecture only. These groups can take on various structures, with three common approaches: Think Pair Share, Peer Instruction, and Jigsaw (Johnson *et al.*, 2014); see Section 3.2.

As we will see in Section 3.2.2.1 and 3.2.1.2, there are several phases to each of the two work styles, which have different communication needs.

Collaborative teamwork has many types. For example, teams collaborate to solve complex projects by sharing knowledge and skills. Individuals with common interests collaborate in design thinking and problem-solving and form what is known as communities of practice. In addition, online tools and communication platforms are used to provide real-time collaboration and track progress in virtual collaborative teamwork (Wenger, 1999; Hertel *et al.*, 2005; Bell, 2010; Leavy, 2012).

Regarding the communication needs of the various work styles, it should be noted that communication can take various forms, including face-to-face talks, calls, emails, instant messages, and video conferences. These fall along different communication *types*; table 2.1 lists the various communication *types*, along with example tools and their advantages. Effective communication requires active listening, clear expression of ideas, and adapting to different communication styles and preferences. One of the essential things related to communication is understanding the goal behind the communication, whether it is for problem-solving, decision-making, teamwork tasks/projects, or information sharing. Another aspect is the period of communication team needs, whether it is regular meetings or periodic meetings. Different situations require different communication styles. For example, some teamwork projects are more convenient with virtual rather than face-to-face meetings. Group work in learning requires constant communication to allow individual students to express and share thoughts with others.

Both modalities of teamwork, collaborative and cooperative, may employ similar tools for achieving their respective goals, while the extent to which communication and collaboration are emphasised may differ. In collaborative tasks, tools like Google Documents, Trello, Microsoft Teams, Dropbox, and Zoom are mentioned for file sharing, task management, deadline tracking, and enhanced communication and collaboration. Similarly, tools such as Zoom, Google Meet, Telegram, and Skype are highlighted for cooperative group tasks, emphasising communication and virtual meetings (Kirschner et Karpinski, 2010). Additionally, the mention of social media as a potential tool for learning purposes echoes the concept of utilising synchronous and asynchronous capabilities for communication and collaboration, as seen in the video and online classes for synchronous communication and the ability to interact independently of time and place for asynchronous communication. These tools provide a range of features to facilitate collaborative and cooperative learning experiences essential for effective communication and collaboration in both modalities of teamwork, enabling students to interact, communicate, and learn together effectively, whether physically present or in virtual settings (Giannikas, 2020); see Section 3.5.

Communication Type	**Example**	**Advantage**
Face-to-Face	In person meetings	Immediate feedback
Online/Virtual	Virtual meetings	Remote work regardless of geographical location
Email(Asynchronous)	Formal messages and shared documents	Having written records
Instant Messaging	Informal messages and Urgent queries	Realtime conversations.

Table 2.1 Different Communication Types

2.4 Characterizing Group Work Dysfunctions ($O_{2.1}$)

Successful organizations are rooted in effective teamwork. Several factors affect the teams' performance, in both small and large organizations. Lencioni identified them as teamwork dysfunctions (Lencioni, 2012). The description of team dysfunctions, and how they manifest themselves in team interactions are described in Section 5.2. For the purposes of this chapter, we will highlight the major findings from Section 5.2.

Lencioni presented the dysfunctions as a pyramid where the dysfunction at one level induces dysfunction at the level above it, in a sort of a causal chain (Lencioni, 2012). The five dysfunctions start from Absence of *Trust*, Fear of *Conflict*, Lack of *Commitment*, Avoidance of *Accountability*, and Inattention to Results (Lencioni, 2012). Table 2.2 lists the characteristics of teamwork dysfunctions along with their effects; a more detailed description of each dysfunction is provided in Section 5.2

Dysfunction	Characteristics	Effects
Absence of Trust	Team members are not open to each other about mistakes and weaknesses. They hold grudges and hidden feelings.	Unhealthy working environment that hinders collaboration
Fear of Conflict	No constructive team debates and avoiding healthy conflicts.	It hinders the team's ability to confront essential issues.
Lack of Commitment	Not committed to plans and goals and discussing the same things.	Failure to achieve common goals.
Avoidance of Accountability	Teams do not hold themselves or other team members accountable for counterproductive situations.	Missing the goals and lowering individual and team performance.
In attention to Results	Prioritise individual success over team success.	Poor performance that affect the group success.

Table 2.2 Characterizing Teamwork Dysfunctions

Many of the characteristics associated with the dysfunctions will manifest themselves in interactions between team members. When those interactions are verbal, and leave a textual trace, we hypothesize that we may be able to detect the dysfunction characteristics by analyzing the interactions' textual traces using *sentiment analysis techniques*. The next section (2.5) introduces sentiment analysis techniques, and the one after that explores how such techniques can be used for detecting team dysfunctions.

2.5 Sentiment analysis techniques - An introduction

Sentiment analysis is a subdomain of natural language processing. It is the systematic procedure of identifying and classifying text emotional expressions. It is used widely in business marketing and organisations as they grow more aware of the importance of group work success. There are various uses of sentiment analysis, for example, to assess customer reviews or feedback to predict customer satisfaction with a service or product. Analysing political opinions in social media posts and categorising them into positive, negative, and neutral is another use of sentiment analysis (Taherdoost et Madanchian, 2023; Taboada, 2016).

Sentiment analysis uses many strategies to detect the emotional sentiment included in text data. The familiar machine learning method is supervised learning, where we train the model on a labelled dataset and then on new, unseen data to predict the sentiment labels, which could be positive, negative, or neutral, the main categories of sentiments. The prediction is based on the patterns learned from the labelled examples during training. The other machine learning method is unsupervised learning; in this approach, we do not have a labelled dataset; the model identifies patterns and groups similar textual data such as K-means clustering, grouping similar data points. The unsupervised method helps discover patterns, relationships, and structures within data without needing labelled examples. The choice of method depends on the specific needs and complexities of the analysis we have (Haddi *et al.*, 2013; Pathak et Rai, 2023). The following are the main sentiment analysis methods:

- Machine learning methods, such as supervised learning, use labelled datasets to train models for predicting sentiments in unseen text, whereas unsupervised learning clusters the text without explicit labels (Devika *et al.*, 2016).
- Lexical-based methods use sentiment dictionaries to assign polarity scores to words, determining the overall sentiment (Devika *et al.*, 2016).

- Rule-based methods use predefined linguistic rules to distinguish sentiments based on keywords and patterns (Devika *et al.*, 2016).

Sentiment analysis depends on text processing techniques. These techniques involve many processes, beginning with tokenisation, which divides text into separate units like words or characters. Stemming and lemmatisation are employed to reduce words to their base forms, enhance consistency and decrease dimensionality. Refining text data requires noise reduction techniques, such as eliminating stop-words and managing punctuation and special characters. Feature extraction techniques, such as Bag-of-Words, TF-IDF, and word embeddings, allow text conversion into organised representations suitable for analysis. All text processing techniques are essential for sentiment analysis as they enable the models to classify texts to the correct sentiment, speed up the classification process, and lead to improved model performance and accuracy. (Haddi *et al.*, 2013)

2.6 Using sentiment analysis to recognise team dysfunctions ($O_{2.3}$)

Our hypothesis is that the five teamwork dysfunctions will: 1) manifest themselves within team communication, and 2) have different "signatures". This is based on Lencioni's work (Lencioni, 2012), who identified the most common utterances that are indicative of each dysfunction. For example, one way to know that a team suffers from the *absence of trust* dysfunction is that team members asking for help use guarded language. Another way to think about *fear of conflict* dysfunction is that team members avoid engaging in a passionate, unfiltered, and constructive debate about every topic relevant to the team's performance. One way to recognize *lack of commitment* dysfunction is through a team's ambiguity, indecision, or a lack of clear assignment and acceptance of tasks and responsibilities. Team members use vague language to discuss deadlines, goals, or action plans. We may even see a lack of enthusiasm or motivation.

It is still challenging to determine the presence or absence of these dysfunctions based on how team members speak to one another. Indeed, identifying and quantifying whether or not those dysfunctions occur remains a significant problem within teams, particularly in real-time (Lencioni, 2012). Current methods rely almost exclusively on subjective assessments by the team leader or post-hoc analyses (after they have become leviathans), both of which are inordinately time-consuming and naturally biased. There is a pressing need for a model that can provide an objective, scalable, efficient approach to classifying and dealing with these dysfunctions as they occur within interpersonal dialogues in real-time (Martínez-Moreno *et al.*, 2009). The automated approach through sentiment analysis and machine learning injects objectivity and efficiency by using algorithms trained on labelled data; machine learning can adapt to a wide range of datasets and learn from data patterns, allowing us to delve into data for subtle cues that might be missed by human eyes and achieve a fuller understanding of teamwork dynamics.

Because there are five different dysfunctions, which may manifest themselves to varying degrees in team communication, we see two general strategies for identifying them with machine learning:

1. A single machine learning model that recognises all dysfunctions in team communication simultaneously through multi-class classification. In this approach, a machine learning model is trained to identify various teamwork dysfunctions in one go. The model can identify all possible teamwork dysfunctions through learning patterns and features from the data, but it poses several challenges. It may be challenging to train a single model that accurately captures all types of dysfunction, mainly if these dysfunctions exhibit diverse underlying patterns. The conversation or dialogue could have more than one dysfunction. It could confuse the model when accurately classifying the dialogue or discussion. In addition, specific dysfunctions may differ significantly in their prevalence in the data. They could lead to class imbalance problems, where the model performs well on the over-represented types of dysfunction and poorly on others.

2. Using multiple models, each one aimed at detecting one particular dysfunction at a time through binary classification (presence or absence of dysfunction) or a graded classification that rates the severity of dysfunctions. This approach trains a distinctive machine-learning model for each teamwork dysfunction. Each model is used separately to detect the presence and severity of a particular dysfunction. As a result, the model can concentrate on the unique features and patterns associated with that specific dysfunction. By doing this, we gain several benefits. It allows us to specialize the models for each dysfunction, which may

enhance performance in detecting particular issues, making the interpretation and diagnosis of dysfunctions much easier. Because each model only concentrates on a single aspect of teamwork, it's obvious how much any one factor contributes to the overall functioning of the team.

Before delving into the specifics of our chosen approach, providing an academic context for how teamwork is evaluated is essential. Lencioni's model is an insightful lens for understanding how teamwork is evaluated. He created a model to help teams identify and correct the problems that prevent them from succeeding. He detailed his organizational model in his book *The Five Dysfunctions of a Team*(Lencioni, 2012). The model identifies the five major issues that cause teams to *misfire*. To find out just how badly these dysfunctions are hurting your team, Lencioni developed a survey. It is a simple questionnaire designed to identify the presence of the five dysfunctions. Teammates fill it out, and then team leaders or facilitators look at their answers and determine how the team is doing in these five key areas. The results are calculated by taking the average score. If the score is high, it means the team is doing well. If it is low, some problems need fixing. A medium score suggests some mixed feelings or uncertainties within the team (Lencioni, 2012).

Building upon this groundwork, we selected the second 'multiple-models' approach by training five different models, on per dysfunction, detect its presence and severity (low, medium, high). Doing so makes it possible to classify each dysfunction in the conversation or dialogue accurately. Training the models one dysfunction at a time lets them learn the unique patterns and feature space for each teamwork dysfunction. It results in highly accurate identification and understanding of the underlying issues.

The sentiment analysis approach to identify teamwork dysfunctions in student dialogue involves leveraging natural language processing (NLP) and machine learning techniques to analyse the sentiments expressed in written communication among team members. To do so, we need relevant textual data that captures team interactions. This data represents the communication channels between team members, such as chats, email exchanges between groups, feedback exchanges and many other communication text exchanges. Finding a high-quality labelled dataset for accurately training machine learning models to identify teamwork dysfunctions is challenging. Many scenarios arise for the data collection process, and they are listed below:

1. If existing text exchanges between team members are available, we need them labelled. However, if they are not labelled, we must manually annotate them. This may require participants to self-report the dysfunctions they perceive in their interactions. We can also have researchers in the field annotate the data by tagging each instance with the corresponding dysfunction category, along with the corresponding score; this will require significant time and effort.

2. If we need to capture new text exchanges, we should obtain consent from student groups to share their team exchanges by explaining the purpose of the experiment, ensuring transparency about data usage, and addressing privacy concerns. It's essential to obtain informed consent from participants. However, informing students about the purpose of the experiment could influence their communication behaviour; therefore, we need to reassure them that their contributions will be anonymised and used for research purposes only.

3. The language issue. Suppose the students agree to share their text exchanges. In this case, we may face language issues because they will be in French at UQAM, which involves annotating them manually. Thus, we must train machine learning models in French to ensure accurate analysis.

As discussed earlier to avoid the potential confusion that could arise when dealing with conversations or dialogues containing multiple dysfunctions. We decided to apply the multiple model training approach, but it requires five different datasets, each representing a dysfunction with the corresponding level scores(low, medium, high). However, finding the right datasets for each of the five teamwork dysfunctions, with labels indicating their severity levels (low, medium, high), isn't easy. We've searched through dataset repositories but haven't found exactly what we need. This lack of suitable data presents a significant obstacle. In the next section, we'll discuss how we plan to tackle this problem and come up with solutions 2.7.

2.7 Building a dataset labelled with team dysfunctions ($O_{2.3.2}$)

Building a trained model for sentiment analysis requires a good-quality training dataset. Data collection is an essential aspect of building a trained machine-learning model. Many data resources exist, such as social media platforms, customer web reviews, and data repositories like Kaggle, GitHub, and the UCI Machine Learning repository.

Finding suitable datasets was challenging. Because we were going to use *supervised learning* methods, we needed labelled data that covers the five teamwork dysfunctions. Finding such comprehensive data proved difficult. In our search, we came across the Enron dataset, which initially seemed promising. Indeed, the Enron dataset consisted of email exchanges between Enron employees prior to the accounting scandal that led to its bankruptcy (Cohen, 2023); these exchanges were believed to reflect the dysfunctional company culture that eventually led to its demise. However, the Enron dataset had two major problems, discussed further below.

The first problem is the fact that it was not labelled: the different email exchanges were *not* labelled with the team dysfunctions. We considered using it with zero-shot learning, an approach wherein we train models without using any labelled examples. When we tried to validate manually the labels assigned by the model using zero-shot learning, we realized that the human subjects who did the validation did not agree on the labels. The main reason was that the emails themselves did not represent exchanges but simple one-way communications, and this was the second problem with the data set. Accordingly, the human subjects who tried to label the email trails with the team dysfunctions had to "read between the lines" to guess at the underlying dysfunction and often came up with different inferences. The Enron experiment is detailed in Chapter 4

Given these problems, we explored using ChatGPT to generate dialogues that exhibited the desired dysfunctions, given the *right prompts*; this is described in Chapter 5. ChatGPT is an AI chatbot from OpenAI, built on the GPT-3.5 architecture from their Generative Pre-trained Transformer series. ChatGPT is an *autoregressive language model*, i.e. a deep learning model concerned with handling sequences (or series) of natural language processing (NLP) tasks; as input, it takes human prompts and produces AI-generated content, such as text, images or video, that resembles more or less closely what humans would produce. We hypothesized that, given a precise characterization of the various dysfunctions, we might be able to generate imaginary dialogues between members of a team that suffers from a particular dysfunction, that exhibited manifestations of those dysfunctions, which could then help train a machine learning model.

In order to do this, we needed to first arrive at a more detailed characterization of the five dysfunctions, and more specifically, identifying how those dysfunctions manifested themselves in dialogues. Fortunately, Lencioni had proposed a *team assessment tool* that associates each dysfunction with a set of *behaviors* that manifest themselves in member communications (Lencioni, 2012). For example, regarding the *lack of trust* dysfunction, some of the signs include that: 1) members rarely or never admit their mistakes, 2) team members rarely tap into each other's skills and expertise, etc. Accordingly, we could–in principle–prompt ChatGPT to generate dialogues that exhibited these two behaviors (rarely/never admitting mistakes, rarely/never tapping into others' skills)–and the remaining six identified by Lencioni for lack of trust (Lencioni, 2012, p. 197). The five team dysfunctions, and how they manifest themselves in team dialogues are presented in Section 5.2.

For each team dysfunction (lack of trust, fear of conflict, lack of commitment, lack accountability, inattention to results), we generated close to 200 dialogues, about evenly divided between three levels of dysfunction (low, medium, high), for a total of 1000 dialogues (see Section 5.4). We first experimented with ChatGPT's GUI, to refine the methodology and the prompts, and then used the ChatGPT API (see Section 5.3.

Now that we generated dialogues that (are supposed to) exhibit team dysfunctions, we need to *manually validate* the dialogue labels, i.e. we need to ask *human subjects* to check whether, say, a dialogue generated by ChatGPT based on the "team members rarely admit mistakes" prompt, do indeed exhibit lack of trust. A preliminary validation is described in Section 5.5.

We did not obtain perfect agreement between the ChatGPT-assigned labels and those assigned by human subjects. These human subjects also lacked high-enough agreement among themselves. However, we felt the dataset still provided a good basis for model training (Section 5.6).

2.8 Conclusion

This chapter provided an overview of the research methodology employed in this thesis. It began with an overview of the research problem derived from our theoretical extension of the five teamwork dysfunctions. The extension led us to hypothesize that these five dysfunctions would emerge within team communication and produce distinct “signatures”. This hypothesis fueled our exploration of the communication needs and team dysfunctions, which resulted in developing a sentiment analysis model based on multiple machine learning classifiers to diagnose these dysfunctions within team communication. We explained how, through theoretical frameworks and empirical analysis combined with machine learning techniques, our systematic approach allows us to illuminate the subtle dynamics of teamwork to understand teamwork dysfunctions that hinder team success in organizational environments.

CHAPTER 3
CHARACTERIZING GROUP WORK

3.1 Group work

For the attainment of common goals, people tend to put effort in the same direction. This effort is described as group effort. The work done by the members of a group is referred to as group work (Brame et Biel, 2015). Many sectors of activities involve large and complex projects that require a wide variety of skills and involve a large number of people. For instance, for construction and architecture organizations, architecture might be needed to design a housing complex, mall or town, in the fashion and design industry stylists and designers might be grouped to execute a fashion show. In public sectors, policymakers and executives cooperate to formulate and execute policies for the welfare of the public. Similarly, students can assemble in groups to complete different academic projects. Projects of students can be of different types like research projects, experimental projects, presentations, group assignments, problem-solving projects, and design projects–where they have to formulate or design certain products (Rosen *et al.*, 2018).

Group work is more important than individual work because it polishes the group members at so many levels and students learn how to convey their ideas effectively so that those can be heard and appreciated (Kirschner *et al.*, 2011). Before the initiation of any group project, many things need to be considered. Accordance to Wilson, when an instructor assigns a group project he or she must look into other matters like the type of group (formal or informal), size of group (small or large), nature of group work (collaborative or cooperative), tasks being performed by the members, tools needed for communication etc. (Wilson *et al.*, 2018)

Group learning is crucial in student life because it aids in the development of certain skills for students at an early stage. Group learning enhances analytical skills, cognitive abilities, social skills and communication skills (Barkley *et al.*, 2014). Depending on the nature of the projects assigned to students there are certain group learning techniques, such as collaborative learning, problem-based learning, cooperative learning, team-based learning, peer instruction and peer tutoring (Davidson et Major, 2014).

In universities, the most common techniques used by students for teamwork are cooperation and collaboration. In some projects, students cooperate so that they can achieve their individual goals while in some projects collaborative effort is put in for the achievement of a common goal of the whole group. For instance, in group presentations, a cooperative effort is evident as every member co-operates with each other but at the same time, everyone is responsible for their portion only. In research-related projects, collaborative effort is required because the whole group will aid in analyzing the gathered information so that results can be derived. Group projects can require both collaboration and cooperation, individuals might cooperate to finalize the portions of individuals and in the end, they collaborate to present the final project (Wilson *et al.*,).

3.2 Cooperation based Teamwork vs Collaboration based Teamwork

Cooperation is when colleagues help each other to achieve the goal of the individual or group while in collaboration people group up to achieve the common goal of a group of people.

3.2.1 Cooperation based Teamwork

The concept of co-operation is quite old amongst the other group work activities and learning. The name originates from the Latin word "cooperat" and, the name suggests, ‘co’ means together and ‘operari’ means to ’work’. So, from the name, it is clear that cooperation is a phenomenon in which people come together to perform some sort of work (Davidson et Major, 2014). If one sees cooperation in the education sector then, it will be regarded as the phenomenon in which students work together to accomplish some sort of project or task. It can be defined as, “the instructional use of small groups to promote students working together to maximize their own and each other’s learning (Johnson et Johnson, 2008). In universities, group work is given importance because it enhances the social skills of the students, and they get to know how to interact with each other and behave in a certain social setting. Cooperative team learning can be both formal and informal, sometimes in this sort of teamwork, the instructor intervenes to make the learning experience better and more meaningful (Johnson et Johnson, 2013).

3.2.1.1 Styles of Cooperation-Based Groups

Cooperative groups can be regarded as informal and formal learning groups.

1. Informal Co-operative Learning Group

   These groups are formed for a limited time duration and are smaller in size, students might co-operate with each other to perform tasks for one lecture only. Informal cooperative groups can be structured in three manners.

   - Think Pair Share In this instructor asks the students certain questions and gives them time to formulate answers, when answers are formulated then students are grouped and asked to discuss their answers with the members and in the last step each group has to share responses with the whole class (Lyman *et al.*, 2023).
   - Peer instruction

     Another grouping manner for informal cooperative groups is a computer-based discussion model. In this multiple-choice question is asked from students have to give a response and after that time is provided to share ideas. After discussion, students can change their computer-generated ideas. In the end, a graph is generated of responses given by students before and after the discussion (Mazur, 1997).
   - Jigsaw

     The third method of informal cooperative learning is the Jigsaw method, in this students are divided into four groups and each group is entitled to a different topic after that these groups are shuffled and asked to discuss topics with each other (Anderson et Palmer, 1988).

2. Formal Co-operative Learning Group

   Formal cooperative learning is for longer periods and students are grouped to finish the assigned task (Johnson *et al.*, 2014). Features of formal cooperative learning groups are;

   - The lecturer defines the key objectives of the groups and formulates the groups.

- Formulated groups are heterogeneous, the main focus is on the skill set of students concerning group tasks.
- The lecturer assigns different roles to the members after discussion with them and the lecturer also elaborates on the skills required for the completion of a task.
- The lecturer plays a chief role in formal cooperative activities and evaluates performance based on group performance and individual performance.

3.2.1.2 Phases of Cooperative Teamwork

Co-operative teamwork is constituted of different phases and these phases are not linear and can overlap each other or one or two phases can be combined depending on the nature of the project. Efficacious results of cooperative teamwork are dependent on individual accountability, appropriate communication, constructive interdependence and supportive interactions among group members (Johnson, 2017). Phases of cooperative group work are elaborated underneath.

1. Forming Phase:

   This is the founding phase of the group. During this phase students are grouped, they get to know each other and introduce themselves to other members. Mutual trust and respect are also developed during this phase. Discussions about the respective project and expectations from that project are held to break the ice among the members.

2. Planning Phase:

   After getting familiarized with each other, the members step into the second phase i.e., the planning phase. In this member sketches the outline of the project and break it into different parts and different tasks are assigned to the individuals. This phase is a blueprint of whole cooperative teamwork. If planning is done smoothly, then it will aid in smooth coordination and communication in the group's next phases.

3. Execution Phase:

   Once the framework is ready, it is time to execute it. All the members cooperate and work together to complete the project and achieve the objectives outlined in the former phases. For successful execution communication and coordination among group members is quintessential (Slavin, 2014).

4. Monitoring Phase:

   Timely feedback and accountability make cooperative teamwork effective. After implementation, the progress and task of every member are assessed by each other and if there is any problem in the accomplishment of a task, it is resolved through teamwork (Slavin, 2014).

5. Reflection Phase:

   The last phase of cooperative teamwork is the reflective phase. In this phase, the work done by every member is evaluated effectively and if there is any loophole left in the project, it is erased. Every member gives their input to minimize the errors in assigned tasks and attain optimal results.

3.2.2 Collaborative Teamwork

Collaboration is working together as a team to achieve a shared goal. Collaborate term was also originated from the Latin word 'Collaborare' 'col means together' and 'laborare means to work'. Collaboration means to do work collectively for the attainment of the same end but that collective effort does not mean the cooperative effort (Davidson et Major, 2014)

3.2.2.1 Phases of Collaborative Teamwork

Collaborating with classmates as a team requires going through various stages that promote effective teamwork and the accomplishment of shared objectives. The following are the different phases of collaborative teamwork:

1. Establishing Goals:

   During this stage, students gather to determine the aims and objectives of their joint project or assignment. They talk about and clarify the purpose, intended results, and specific goals they want to accomplish as a team (Wei et Murphy, 2017). By establishing clear goals, they ensure that everyone is on the same page and working towards a shared direction in their collaboration.

2. Planning and Organization:

   After setting the goals, students proceed to the planning stage where they formulate strategies, create task outlines, and assign responsibilities to team members (Johnson et Johnson, 2013). Effective planning plays a crucial role in coordinating resources and efforts to achieve optimal productivity and efficiency.

3. Communication and Coordination:

   Effective communication is essential for successful collaboration within a team. In collaborative teamwork, students engage in continuous communication, exchanging ideas, sharing information, and providing updates on their progress. They actively listen to one another, seek clarification when needed, and offer constructive feedback to enhance collaboration (Wei et Murphy, 2017). Additionally, coordination efforts are put in place to ensure that all team members are kept informed about the team's progress and any required modifications.

4. Collaboration and Task Execution:

   In this stage, students collaborate and cooperate to accomplish the tasks assigned to them. They make use of their combined knowledge, skills, and perspectives to engage in problem-solving activities together. They share their insights, exchange ideas, and provide mutual support to achieve the desired results. This collaborative approach promotes creativity, and critical thinking, and enhances the depth of their learning experiences (Johnson et Johnson, 2013).

5. Reflection and Evaluation:

   Upon finishing the joint project or assignment, students participate in a process of contemplation and assessment. They evaluate the efficiency of their collaborative efforts, recognize their strengths as well as areas that need improvement, and assess their individual and collective contributions (Wei et Murphy, 2017). Reflection aids in the development of metacognitive abilities and fosters a mindset of ongoing progress and enhancement.

3.2.2.2 Styles of Collaborative Teamwork

Multiple approaches to collaborative teamwork determine the way individuals cooperate, engage with one another, and make contributions toward a common objective. Underneath various styles of collaborative teamwork are discussed,

- Design Thinking:

  Design thinking is a cooperative method of solving problems that prioritizes empathy, iterative brainstorming, and creating prototypes. Members of a team participate in a design process that focuses on the needs of users, working together to gain an understanding of those needs, generate innovative solutions, and create prototypes for testing and addressing the detected challenge (Leavy, 2012)

- Project-Based Collaboration:

  Project-based collaboration entails teams coming together to work on intricate projects or tasks that necessitate a fusion of skills and expertise. Throughout the entire duration of the project, team members engage in collaborative efforts, distributing responsibilities, coordinating actions, and capitalizing on their diverse strengths to accomplish the desired project objectives (Bell, 2010).

- Communities of Practice:

  Communities of practice serve as collaborative frameworks wherein individuals who possess common interests or professional fields converge to acquire knowledge, exchange information, and cultivate proficiency. Within these communities, members actively participate in collaborative discussions, share their experiences, and make contributions towards the collective learning and advancement of the community (Wenger, 1999).

- Virtual Collaboration:

  Virtual collaboration is the process of using digital technologies to enable teams with members located in different geographical locations to work together effectively. It involves utilizing various online tools, communication platforms, and virtual workspaces to engage in both real-time and delayed collaboration, ensuring effective communication and shared progress in the work (Hertel *et al.*, 2005).

3.3 Differences and Similarities between Cooperation and Collaboration

Cooperative and collaborative teamwork possess certain similarities but also demonstrate notable distinctions when it comes to their approaches to working collectively within a team environment. The following discussion highlights the shared traits and disparities between cooperative and collaborative teams, with supporting evidence from relevant sources.

Similarities:

1. Shared Goals:

   Both cooperative and collaborative teams share the same aim of accomplishing a unified goal or objective. Their actions are guided by a shared purpose that directs their endeavors. "In cooperative learning, students work together toward common goals (Johnson et Johnson, 2013).

2. Interdependence:

   Both methods entail a certain degree of mutual reliance among team members, wherein individuals depend on one another's contributions to accomplish the intended result. It is acknowledged that the team's success hinges on the collective endeavors of all its members. "In collaborative learning, learners rely on one another to complete tasks and to be successful" (Slavin, 2014).

Differences:

1. Individual Accountability:

   In cooperative teamwork, it is customary for each team member to have a distinct task or role, thereby establishing individual responsibility. The emphasis is placed on distributing responsibilities among team members and ensuring that each person actively contributes to the overall success of the team (Slavin, 2014)

2. Shared Decision-Making:

   Collaborative teamwork emphasizes the importance of shared decision-making and collective problem-solving. Team members actively contribute their ideas, participate in open discussions, and collectively make decisions that have an impact on the team (Dillenbourg, 1999).

3. Group Dynamics:

   In cooperative teamwork, the approach typically involves the distribution of tasks and the allocation of roles among team members, to accomplish distinct components or subtasks within a project. Conversely, collaborative teamwork places greater emphasis on incorporating various perspectives and leveraging the synergistic effects resulting from team members' interactions (Johnson et Johnson, 2013).

3.4 Collaborative or Cooperative Group Work? Two names of a Single Concept

Previously many scholars have not differentiated between collaborative and cooperative learning. Scholars have used both terms interchangeably to define the group work and distinctive boundaries of both terms were not defined earlier (Resta et Laferrière, 2007). In accordance to some scholars there are more similarities than differences between the two terms and both are sub types of group work (Kirschner *et al.*, 2004). But there is prevalence of certain differences between two terms that makes cooperative learning different from the collaborative learning. Cooperative and collaborative learning are ubiquitous, especially in group activities. In cooperative learning, students are separated into small groups, and the teacher allocates specific roles and tasks to each student, so it is group structured. In collaborative learning, the students agree on the effort among themselves. Correct collaboration is valuable; it allows students to learn from each other, negotiate and improve their academic, communication, and social skills. The collaboration aims to create new insights in discussions and to bring the students closer to understanding alternative perspectives. Important matters to assess if a classroom task is truly collaborative include:

the students negotiating and accommodating one another's perspectives. Everybody contributes equally to ensure that different perspectives are included in the final work (Kozar, 2010). Paulus researched to examine collaborative versus cooperative tasks in an online environment. The study revealed that groups cooperate more than collaborate in group tasks (Paulus, 2005).

Many educationalists have raised questions either these terms should be used interchangeably or each term should be used for specific concept possessing certain characteristics (Brody, 2009). In accordance to some scholars, these are same concepts as both define the characteristics of group work and how individuals perform while working in the group while others argue that cooperation and collaboration are different branches of same origin.

3.5 Tools Used for Cooperative and Collaborative Teamwork

Tools are solely dependent on the specified needs of the members of groups and the project they are working on. For both modalities of teamwork, collaborative and cooperative, tools used can be different or similar. Under a study, for collaborative group tasks, students can use tools like google documents, Trello, Microsoft Teams, Dropbox or Zoom for file sharing, task management, deadlines management, and better communication and collaboration. On the other hand, tools used for cooperative group tasks can be Zoom, google meet, telegram or Skype. In cooperative tasks, more emphasis is on communication and virtual meetings to discuss the project progress (Kirschner et Karpinski, 2010). Social media can also be utilized for learning purposes. Previous studies of social media use in education have focused on specific uses of social media, such as collaborative learning and communication among peers. Many researchers have discussed using social networking sites as learning tools. These studies have shown that social networking sites' main benefits are communication, collaboration, and motivation. However, social networking sites have two characteristics that influence learning development in students and academics and have not yet been explored: synchronous and asynchronous capabilities. An example of synchronous communication is video communication and online classes, in which students and professors can meet online, discuss, and at the same time work together regardless of location. The second key feature of social media is its asynchronous role, allowing teachers and students to send, receive, interact, and collaborate independently of time and place. Giannikas suggests that future research should examine different functions and uses in social media to distinguish their unique uses in the university context (Giannikas, 2020), whereas Khan et al. recommended that future research be conducted with teachers to comprehend their perspectives on the acceptance of social media for collaborative learning (Khan *et al.*, 2021).

3.5.1 Tools for Collaborative Teamwork

Collaborative teamwork requires coordination, communication, and integration of group members inside or outside the university. To make this possible, different tools are being incorporated which make it easier to connect with the group members (Hidayanto et Setyady, 2014). Tools being used are videoconferencing, e-mails, project management tools, wiki, learning management systems, document management software, teleconferencing, web-based tools etc (Aaltonen et Kallinikos, 2012).Usage of technology to achieve collaborative tasks increases the productivity of group members because the group can interact and discuss the agenda at any time and it is not necessary for all members to gather at one place, they can gather virtually at any time (Elie-Dit-Cosaque et Pallud, 2012; Patel *et al.*, 2012; Majumdar et Krishna, 2012; García-Valcárcel-Muñoz-Repiso *et al.*, 2014)

3.5.2 Tools for Cooperative Teamwork

For cooperative teamwork, the most convenient and reliable tool is the face-to-face interaction of members. Through face-to-face interaction, both verbal and non-verbal body language of group members can be analyzed (Johnson *et al.*, 2014). Now, as technology is rapidly changing and it is a technology that world has become a global village and through cloud computing anyone can connect from anywhere at any time (Shi *et al.*, 2014). Students using technology for communication in cooperative group work tend to face more challenges in coordination and communication as compared to students using traditional approaches (Smith *et al.*, 2011; Breuer *et al.*, 2016). In accordance with some theorists, face-to-face interaction is effective tool for cooperative team projects than the modern tools of interaction (Behrend *et al.*, 2011; He *et al.*, 2011; Johnson *et al.*, 2014; Musavengane et Kloppers, 2020). But on the other hand some theorists supports the notion that every field is technologically growing faster and traditional approaches are being replaced by the modern ones so same is happening with team work approaches. Traditionally face-to-face interactions were considered efficient and sufficient but now virtual interactions, technologically advanced and computer-supported meetings have taken the place of physical meetings. Technologically advanced meetings can facilitate the process of sharing ideas and the means of cooperation to accomplish mutual goal. It aids students to interact with each other who are not physically present at the same place, subtasks, ideas and share information though different online tools, it saves time, energy and cost of physical meetings(Jones *et al.*, 2006; Resta et Laferrière, 2007; Chu et Kennedy, 2011; Perron et Sellers, 2011; Olesen, 2020), In cooperative tasks, lots of interaction is not quintessential as every individual is focused on performing one's assigned task so virtual meetings can play a huge role in assembling of the sub-tasks.

3.6 Conclusion

This chapter explains what group work means with examples from different sectors. We revealed various group learning techniques, such as collaboration and cooperation, and the differences between each approach, mainly since previous literature(mostly old ones) uses both terms interchangeably without differentiating the distinct characteristics and recognizing that both comprise a shared conceptual framework(group work). We also showed the styles and phases of each group work modality. We illustrated the tools for cooperation and collaboration, and we found that the choice of the tools relies heavily on the specific needs of team members and the nature of the project/task. Cooperative projects could occur using virtual meetings since each team member is responsible for a particular part(individual effort). In the end, the team will gather all the work for a deposit, whereas, in collaborative tasks, team members may need more face-to-face meetings(or real-time) to discuss the work and help each other achieve their common goal. It is a joint effort. Ultimately, whether a team opts for collaborative or cooperative methods depends on the mission's nature and the desired outcome.

CHAPTER 4

THE ENRON DATA SET AS THE BASIS FOR MODEL TRAINING

Our research involves training a machine-learning model that can identify teamwork dysfunctions in written communication between team members. Identifying and preparing an appropriate *training* dataset is crucial to achieve our goal. The dataset we seek should consist of textual traces that mirror real-world interactions within team settings. The dataset should exhibit the following characteristics:

1. It should consist of dialogues between colleagues working together on a joint project or common goals.
2. It should include communications between coworkers who are part of teams that exhibit one or several of the team dysfunctions discussed in Section 5.2–absence of trust, fear of conflict, lack of commitment, avoidance of accountability, and inattention to results.
3. The dialogues should be labeled by the kinds of dysfunctions that they exhibit.

In this chapter, we first introduce what dataset we are looking for, present the Enron dataset and give an overview of it and its significance as a base for model training in the context of email exchanges between teams. Then, we introduce the zero-shot classification as a base for getting the Enron dataset labelled with team dysfunctions as identified by Lencioni (Lencioni, 2012). We explain the labelling of the text messages between Enron employees and show the scores we obtained after using the BERT model, which leads us to conclude that the labels were not qualified for model training. We need to think of better data that fits our goal: a dialogue between team members in the context of teamwork dysfunctions. Our conclusion is presented in Section 4.4.

4.1 An Overview of the Enron Dataset

We did a literature search to identify a dataset that satisfies the requirements presented above. A preliminary search identified no such *labelled* data set. However, we came upon the so-called

Enron dataset, which is a dataset consisting of over 500,000 email exchanges between Enron employees, a US-based company that operated mainly in the energy trading market. The dataset was deemed interesting because Enron went bankrupt in December of 2001 following an accounting scandal inwhich Enron employees of all levels in the hierarchy conspired and colluded to distort the company's performance. We felt these email exchanges might exhibit the kinds of dysfunctions we were looking for (see also Section 5.2).

According to New York Times, the fall of Enron in 2001 was not just about money. It was about a corporate culture of lies, cheating and secret deals. Company executives, as well as rank-and-file employees, were busy with shady accounting tricks to make Enron look like a more profitable company than it was. It was all that dishonesty that led to Enron's demise. At the request of the affected employees, parts of the emails (e.g. attachments) have been removed. While some data is missing, it is still a unique and invaluable resource for researchers in data science, machine learning, and social scientists. Therefore, we felt the Enron dataset would offer a great opportunity to explore teamwork dysfunctions. The source of the dataset is available at (Cohen, 2023) and is accessible at `https://www.kaggle.com/datasets/wcukierski/enron-email-dataset`

4.2 An overview of the methodology

While the dataset contains team communications in the form of email trails between Enron employees or Enron employees with external business partners, those exchanges were not labelled by the team dysfunctions. Thus, our first goal was to label the dataset with the team dysfunctions. Thus, we considered using *zero-shot classification*. By leveraging sophisticated natural language processing (NLP) techniques and using BERT-based model provided through the Hugging Face Transformers library, we aimed to predict the presence of five teamwork dysfunctions outlined by Lencioni: absence of trust, fear of conflict, lack of commitment, avoidance of accountability, and inattention to results. Using this method, we thought that we would be able to label each email exchange with the most salient dysfunction that it exhibited.

4.2.1 Using zero-shot learning with the Enron data set.

Zero-shot learning aims to understand and classify unseen data the model has never seen before. It is a helpful method if the dataset is unlabeled. They classify the data set based on the concept of semantics. Zero-shot classification enables a model to predict classes it has never encountered during training. In our case, the Enron dataset, which includes email exchanges among employees and external partners, did not come with pre-assigned labels that designate instances of these team dysfunctions taking place. The zero-shot classification relies on pre-trained models; therefore, we should decide which model is appropriate for our goal before applying it. The model choice affects the results gained regarding how reliable they are. In addition, we should consider the model architecture, size, performance and the constraints we may face, such as computational resources, because some models may be more resource-intensive than others, requiring more powerful hardware or longer training times. Therefore, understanding the computational requirements of different models is very important.

Several language models like GPT, BERT, RoBERTa, and many more exist. During pre-training, these models are exposed to vast amounts of text data, where they learn to predict the next word in a sequence given the context provided by preceding words. This unsupervised learning process enables the models to embody the semantics, syntax, and contextual relationships within natural language. We selected a BERT (Bidirectional Encoder Representations from Transformers), a natural language processing model made available by the Hugging Face Transformers library. The BERT model is available at `https://huggingface.co/docs/transformers/model_doc/bert`, which has been pre-trained on vast amounts of text data, including a large book corpus and Wikipedia. BERT can understand human language and make guesses about its input. However, the key characteristic of zero-shot classification that sets it apart is that it can classify text it had never seen during training.

We selected the BERT model to apply zero-shot classification; the next step is defining the classification labels. Zero-shot classification requires candidate labels to make predictions effectively. In our case, we aim to label the Enron dataset with the five teamwork dysfunctions identified by Lencioni. Our labels are absence of trust, fear of conflict, lack of commitment, avoidance of accountability, and inattention to results. By defining the candidate labels, we establish the framework for classifying text instances from the Enron dataset based on the semantic similarity between the input text (email message) and each candidate label (dysfunction).

4.2.2 A Look at Hugging Face Platform

Hugging Face is a machine learning and data science platform that allows users to build, deploy, and train machine learning models. It hosts many machine-learning models, datasets, and demos. Unlike other closed sources like OpenAI's chatGPT, it is an open platform that allows users to use the code behind the different models. The models are large language models, image models and audio models. It is a hub with rich datasets for NLP and machine learning tasks. It provides a transformer library that simplifies the implementation of NLP models and allows developers to integrate these models into specific applications. The full details of the platform are available at: https://huggingface.co/

4.2.3 Email labeling process

The following steps included the complete experimental analysis of the Enron Dataset:

1. *Data pre-processing*. Before the data labelling process, specific pre-processing steps are required to guarantee the cleanliness and consistency of the textual email messages. Data pre-processing reduces the noise and outliers in raw text data, such as special characters and irrelevant symbols, making the data cleaner and more manageable and enabling more accurate classification.

    - Remove meta-data from email messages. Raw email text messages contains lots of metadata, including headers using by mail processing programs for mail routing, and the like. The metadata does not help with model training. We need to remove meta-data in our case to focus on the content of the messages rather than irrelevant information. The main objective is to extract meaningful information and remove irrelevant or unnecessary details. Figure 4.1 shows the Enron Email dataset, which contains metadata at the start of every email message.

```
Message-ID: <15464986.1075855378456.JavaMail.evans@thyme>
Date: Fri, 4 May 2001 13:51:00 -0700 (PDT)
From: phillip.allen@enron.com
To: john.lavorato@enron.com
Subject: Re:
Mime-Version: 1.0
Content-Type: text/plain; charset=us-ascii
Content-Transfer-Encoding: 7bit
X-From: Phillip K Allen
X-To: John J Lavorato <John J Lavorato/ENRON@enronXgate@ENRON>
X-cc:
X-bcc:
X-Folder: \Phillip_Allen_Jan2002_1\Allen, Phillip K.\'Sent Mail
X-Origin: Allen-P
X-FileName: pallen (Non-Privileged).pst
```

Figure 4.1 Meta data at the start of email message

- Removing URLs from email messages. URLs are not likely to help identify teamwork dysfunctions, so removing them helps maintain text clarity. (Sun *et al.*, 2014).
- Removing Email addresses. Emails often contain personal and sensitive information. In many NLP applications, it is crucial to protect the privacy of individuals. Removing emails helps ensure that personal information is not disclosed or misused (Sun *et al.*, 2014).
- Removing Extra-Spaces within Text. Removing unnecessary white-spaces helps normalize the text and ensures consistency in the representation of textual data, especially with zero-shot classification, which relies on tokenization. Extra spaces affect the tokenization process. Removing them helps maintain a consistent tokenization scheme and improves the model's performance and efficiency.

2. *Data labelling*. The labelling process uses *zero-shot classification*, which lets a large language model predict which dysfunction was behind each email message without training it explic-

itly in each dysfunction. We made a list of candidate labels representing the five teamwork dysfunctions identified by Lencioni. We would want to classify the Enron communication data into these potential categories. A language model called BERT can understand human language in email messages and those possible dysfunctions. It ran through the list of possible dysfunctions for each email message, assigning a probability score to each one that indicated how likely it was to apply to the message. The one that had the highest score was the model's predicted dysfunction for that email message.

3. *BERT for labelling*. Many zero-shot classification models exist on the GitHub repository website. Selecting the best model for the specific task depends on the nature of the task, the dataset, and the computational resources. We used the BERT (bert-base-uncased) model to ease the classification of teamwork dysfunctions within the Enron dataset. BERT stands for Bidirectional Encoder Representations from Transformers. It has been pre-trained on a vast corpus of text data using unsupervised learning objectives such as masked language modelling and next-sentence prediction over a 3.3B word (Tenney *et al.*, 2019). It is the one used and is considered a better model than earlier due to its advantages. This pre-training process equips BERT with some level of language semantics and contextual relationships, making it particularly well-suited for natural language processing tasks(Devlin *et al.*, 2019).

   The method involves pre-training the BERT model without fine-tuning (Further training on the specific classes we seek). This approach relies on the transfer learning concept, where we utilise knowledge from a pre-trained model to assist us in our target. We assumed that transferring BERT knowledge to our goal (classifying text email messages) would enable us to identify and categorise dysfunctions in the Enron dataset. Transfer learning consists of a two-phase learning procedure: pre-training to get knowledge from source tasks and fine-tuning to utilise this knowledge on target activities (Devlin *et al.*, 2019)

   here diagram!?

   - Labeling at Chunk level. Since the Enron email dataset is large and contains $\approx$ 500,000 email samples, we need a resource-efficient system to label this data. Google Colabpro+ provides TPU (Text Processing Unit) resources and compute units. For this purpose, we divided the whole dataset into 10000 email chunks, and performed the labelling chunk by chunk. This technique does not affect the overall labelling since each example is processed by the model independently, and the labels/probabilities are predicted. The labels/probabilities of examples within the dataset are not linked. I divided the dataset into 52 chunks of equal size, having 10000 examples in each chunk. Each chunk was processed separately for labelling and took between one and two hours for data labelling.

- *Ethical Considerations*. We removed chunk #23 from the Enron dataset because of its inappropriate wording; it contains offensive language. In order to fully reap the benefits of AI while maintaining social norms and principles, limiting harm, and guaranteeing fairness, we must consider ethical considerations while putting AI algorithms into practice.

4.2.4 Validating the labeling

After getting the labelled dataset for the email exchanges of the Enron dataset, it is essential to test the reliability of the labels. Here, human judgment acts as the gold standard.

Obviously, we cannot validate all of the 52,000 dialogues. Thus, we need to validate a reasonably size, and representative, sample of the data set.

Our strategy was to proceed in two phases:

1. In the first phase, we do a limited scope, preliminary evaluation, with a small dialogue sample size, and a small number of human subjects, with two objectives in mind:
   (a) Get a preliminary idea about the performance level of BERT, with three potential outcomes: a) high performance, and thus proceed with phase two (more thorough validation), b) mid-level performance, and thus iteratively fine-tune the labeling to enhance the performance, or c) poor, non-salvageable performance, and thus, give up on BERT or the data set
   (b) Design and refine the experimental protocol for phase two.

2. In the second phase, conduct a controlled experiment with a larger number of human subjects, and a representative set of dialogues, to get a more reliable assessment of the quality of the labeling.

Naturally, if the results of the first phase suggest that the labeling is not accurate, we would forego phase two, and we have to forego either BERT lebling, or the Enron data set altogether. 4.3.2).

4.3 Results

This section provides an overview of the results obtained from our preliminary experiment on the Enron dataset. We first present the results of labelling the email messages with BERT (Section 4.3.1), then we talk about the manual cross-validation of the labels by human subjects (Section 4.3.2.

4.3.1 BERT Labeling of the Enron Dataset

Table 4.1 shows a sample of three conversations from the Enron dataset. Table 4.2 shows the BERT assigned scores for the various dysfunctions. According to the BERT documentation, candidate labels of the conversation derived from the results of zero-shot classification (BERT model) are sorted by increasing score, and we take the label(s) with the highest scores.

However, as can be seen from the sample in Table 4.2:

1. All the scores are below 30 %
2. For any given dialogue, the five dysfunction labels get similar (close) scores–most between the high teens and low twenties.

No.	**Conversation**
1	Traveling to have a business meeting takes the fun out of the trip. Especially if you have to prepare a presentation. I would suggest holding the business plan meetings here then take a trip without any formal business meetings. I would even try and get some honest opinions on whether a trip is even desired or necessary. As far as the business meetings, I think it would be more productive to try and stimulate discussions across the different groups about what is working and what is not. Too often the presenter speaks and the others are quiet just waiting for their turn. The meetings might be better if held in a round table discussion format. My suggestion for where to go is Austin. Play golf and rent a ski boat and jet ski's. Flying somewhere takes too much time.
2	Jeff, Is the closing today? After reviewing the agreement. I find it isn't binding as far as I can determine. It is too vague and it doesn't sound like anything an attorney or title company would draft for a real estate closing but, of course, I could be wrong. If this closing is going to take place without this agreement then there is no point in me following up on this document's validity. I will just need to go back to my closing documents and see what's there and find out where I am with that and deal with this as best I can. I guess I was expecting something that would be an exhibit to a recordable document or something a little more exact, or rathersort of a contract. I really do not want to hold up anything or generate more work for myself and I don't want to insult or annoy anyone but this paper really doesn't seem to be something required for a closing. In the event you do need my signature on something like this I would rather have time to have it reviewed before I accept it.
3	As discussed during our phone conversation, In a Parallon 75 microturbine power generation deal for a national accounts customer, I am developing a proposal to sell power to customer at fixed or collar/floor price. To do so I need a corresponding term gas price for same. using natural gas. In doing so, I need your best fixed price forward gas price deal for one two and ten years for annual seasonal supply to microturbines to generate fixed kWh for customer. We have the opportunity to sell customer kWhs using microturbine or sell them turbines themselves. kWh deal must have limited/ no risk forward gas price to make deal work.

Table 4.1 Example of the Conversations

No.	Trust score	Conflict score	Accountability score	Commitment score	Results score
1	0.235864	0.244670	0.179403	0.140625	0.199439
2	0.155699	0.231393	0.147264	0.237848	0.227796
3	0.183770	0.146750	0.158706	0.211431	0.299342

Table 4.2 Candidate label scores for the conversations in Table 4.1.

We had meant to validate the BERT assigned labels manually. These results make it even more critical to do so.

4.3.2 Manual labeling by human subjects

Following the validation protocol discussed in Section 4.2.4, we started phase one of the validation protocol with:

- A sample of 30 email exchanges from the Enron data set, taken to be minimally representative of the length distribution of email exchanges
- Three human subjects, consisting of the candidate and her research advisers.

The researchers were instructed to assign 5 different scores to each email in the sample data set, each score corresponding to one of the five teamwork *dimensions* that Lencioni identified: trust, (healthy) conflict, commitment, accountability, and attention to results. For each dimension, the researchers were to assign a score from a Likert scale (1 to 5) indicating the *performance level* of the team along that dimension, where:

- 1 meant (very) weak performance, which equates with a *high level of dysfunction*;
- 3 meant average performance;

- 5 meant (very) high performance, along that dimension, and
- NA, meaning non-applicable, which meant that the email exchange at hand did *not* provide *any* indication as to the performance of the team along the dimension at hand.

The researchers had many problems assigning scores and had several email exchanges about how to proceed. In particular, the NA label was added as part of those discussions.

Table 4.3 shows the results of the manual validation for one of the conversations (conversation#1). The column 'Subject average' averaged the scores assigned by the human subjects, excluding NA values.

Dysfunction	$Subject_1$	$Subject_2$	$Subject_3$	Subject average	BERT Score
Trust	3	2	NA	2.5	0.235864
Conflict	4	2	NA	3.0	0.244670
Commitment	4	NA	1	2.5	0.179403
Accountability	NA	NA	2	2	0.140625
Attention to results	4	4	1	3	0.199439

Table 4.3 Manual Labeling of Conversation Number 1

The results for conversation number 1, which are indicative of other conversations, show many problems that reflect some of the discussions the researchers had while conducting the experiment:

1. First, they show a significant disagreement between the subjects. For example, for the *Trust* dimension, $Subject_1$ thought that the 'conversation' exhibited an acceptable level of trust, $Subject_2$ thought of a lower level of trust, whereas $Subject_3$ felt that 'conversation 1' did not exhibit any indication related to trust (NA label). The case of 'Commitment' is extreme: $Subject_1$ felt that the 'conversation' showed a high performance (4), $Subject_3$ felt that it

showed mediocre performance (1), and $Subject_2$ felt that the conversation did not address *commitment to results* at all.

2. Unsurprisingly, the average score–whatever that means–bears no (cor)relation to the BERT score.

The discrepancies between the evaluations of the researchers were due, in large part, to the fact that the 'conversation' gave very little indication about team dynamics: they were email exchanges/threads, many consisting of a single email, as shown in Table 4.1. Thus, the three researchers/subjects had to guess, the context of the email–what has preceded it and what may have followed, the roles played by the parties involved (sender, recipients), and 'read between the lines', to see if a sentence or paragraph exhibited a lack of trust, for example.

Finally, while we analyzed the conversations, we did not have precise enough, working definitions of each of the dysfunctions. How does lack of trust manifest itself? Is questioning somebody's decision a sign of lack of trust (negative), or a sign of 'healthy conflict' (positive).

Based on the preliminary results, we decided to not pursue phase two of the validation protocol (Section 4.2.4).

4.4 Conclusion

Lencioni identified five performance dimensions for teamwork (Lencioni, 2012): 1) trust, 2) (healthy) conflict, 3) commitment, 4) accountability, and 5) attention to results. Dysfunctional teams perform poorly along one of several of these dimensions. Our hypothesis is that some of these dysfunctions will manifest themselves in team verbal or written communications, and *should* be recognizable by a properly trained machine learning model using sentiment analysis techniques. Accordingly, our work involves finding or building a properly labeled dataset that consists of a set of written exchanges between members of work teams, exhibiting different levels of performance along the five dimensions identified by Lencioni (Lencioni, 2012).

An extensive search of the web identified no such *labeled* dataset. The internet abounds with reviews of various products and services, and opinion pieces, both labeled and unlabeled. But there are few datasets that included full conversations, and there are *none* that have been labeled by the Lencioni performance dimensions.

At first glance, the *Enron dataset* seemed to solve the first problem: it consists of email exchanges between Enron employees, prior to its bankruptcy. Enron was an American company whose core business was *energy trading*. It has become known for shady business practices, and a corrupt company culture, where employees at different levels of the corporate hierarchy participated in, or tolerated illegal and unethical business practices. Our hope was that the dozens of thousands of email exchanges would exhibit the kinds of team dysfunctions that can foster or tolerate corrupt business practices.

Remains the problem of *labeling* these email exchanges with performance indicators along Lencioni's performance dimensions. To this end, we relied on BERT and zero-shot learning to perform this labeling. Before we could use the so-labeled dataset, we needed to manually validate the BERT-assigned labels by comparing them to labels assigned by human subjects (Section 4.2.4). The preliminary validation identified major problems. This compelled us to take a deeper look at the data set, which revealed its inadequacy for the task at hand (Section 4.3.2). In particular, we realized that the email exchanges consisted mostly of single emails, or a series of email forwards which no actual 'back-and-forth' discussions. Further, it appeared that we were asking/expecting too much of BERT by supplying team performance scores, with little context into what each performance dimension/dysfunction means.

This led me to consider using LLMs to generate dialogues that exhibit the desired performance characteristics (good or bad), using a more precise characterization of each of the performance dimensions/dysfunctions. This is discussed in Chapter 5, next.

CHAPTER 5
USING CHAT GPT TO DEVELOP A TRAINING DATA SET

5.1 What is ChatGPT?

OpenAI's ChatGPT is an artificial intelligence (AI) chatbot that simulates human speech using natural language processing. The GPT-3.5 architecture, or "Generative Pre-trained Transformer 3.5," is its foundation. A family of large-scale language models trained on a variety of online texts to handle a range of tasks related to natural language processing, GPT-3.5 is a member of the GPT series. Generative AI refers to ChatGPT, a technology that allows users to input prompts and receive AI-generated images, text, or videos that resemble people. Because users can ask questions and get clarifications on responses from ChatGPT, it resembles the automated chat services available on customer support websites. Its answers are based on a statistical analysis of content available on the internet until September 2021. "Generative Pre-trained Transformer," or GPT for short, describes how ChatGPT responds to queries and constructs answers.

Reinforcement learning is used in ChatGPT training. The language model may write emails, articles, essays, code, social media postings, and other textual content in addition to responding to queries. The documentation of the details exists on the OpenAI platform's website or developer portal. [1]

ChatGPT/OpenAI can be used in two ways:

- API: Application Programming Interface
- GUI: Graphical User Interface

[1] Visit OpenAI's documentation for comprehensive technical details about using ChatGPT and related resources. https://platform.openai.com/docs/introduction

5.1.1 Which to use API or GUI?

The choice between the OpenAI API and the OpenAI GUI (Graphical User Interface / ChatGPT) depends on your use case, requirements, and preferences. Here are some considerations to help decide when to use the API versus the GUI:

5.1.1.1 Integration into Applications or Services

- API is recommended in cases where we want to integrate and automate ChatGPT in our applications, products or services. It allows for seamless integration and automation.
- GUI is convenient when we need a quick and interactive way to experiment with the model or generate responses without coding.

5.1.1.2 Customization and Control

- Use API: If we require more control over the parameters, settings, and behaviour of the model, using the API allows us to fine-tune the requests and responses based on our specific needs.
- Use GUI: If we are looking for a simple, user-friendly interface without needing advanced customization or control, the GUI provides an easy way to interact with the model.

5.1.1.3 Prototyping and Exploration

- Use API: If we are building a prototype, testing different scenarios, or exploring the capabilities of ChatGPT in a scripted environment, using the API offers more flexibility.
- Use GUI: If we want to quickly try out the model without writing any code and explore its capabilities in a user-friendly interface, the GUI provides an accessible option for experimentation.

5.1.1.4 Batch Processing

- Use API: If we need to process many requests in batch mode or perform bulk operations, using the API allows for the efficient handling of multiple queries.
- Use GUI: If we have only a few queries and prefer a manual, interactive approach, the GUI may be more suitable for occasional use.

5.1.1.5 Cost Considerations

- Use API: If we have specific budget constraints or want to manage costs more effectively, using the API may allow for more control over resource usage and associated expenses.
- Use GUI: If cost is not a primary concern and we prefer the simplicity of a user interface, the GUI can be a straightforward option for occasional use.

5.1.2 Rationale for API Adoption in Dialogue Generation

In the research experiment, we utilised the ChatGPT API to maximum advantage in order to generate dialogues tailored to our specific requirements. The API offered us programmatic access, enabling seamless integration of ChatGPT into our custom needs. This level of programmatic control allowed us to fine-tune the model's responses to align precisely with our research objectives. Furthermore, the API facilitated a high degree of customisation, enabling us to configure ChatGPT to produce dialogues that met our specific criteria and guidelines. This customisation was crucial in ensuring that the generated dialogues were contextually relevant and adhered to the specific conversational patterns and content required for our research. We have tried various models, including ChatGPT-4, which is mainly used for analysing text, images, and voice, but it yields little results for content development. Based on the documentation, ChatGPT-3.5 Turbo is more helpful in generating content and matches our requirements. Moreover, the cost of generating content in 3.5 Turbo is less than GPT-4.

There are two distinct methods to generate content in chatGPT API. They are:

- Completion API (Legacy), which cut off on January 4, 2024
- Chat Completion API (latest)

As completion API (Legacy) ends on January 4, 2024, we have used Chat Completion API because it represents the most recent progress in content generation and ensures the longevity of the code for future reference. Conversely, we also utilised the graphical user interface (GUI) in our experimentation phase. This interface offered a practical and rapid means for manual interactions with ChatGPT. It allowed us to engage with the model, generate responses, and explore potential dialogue scenarios without coding or extensive technical setup. The GUI proved valuable for quick iterations and experimentation as a user-friendly tool for preliminary investigations and generating insights. It is the first step to figure out how to design the prompts to use them in the API implementation(openai, 2023).

In summary, our research experiment showcased the versatility of ChatGPT, where the API served as the preferred choice for programmatic access, customisation, and integration into our specific applications, ensuring precision and control in dialogue generation. Simultaneously, the GUI offered a convenient avenue for swift, manual interactions and experimentation, streamlining our research process and enhancing our understanding of ChatGPT's capabilities.

As explained above 5.1.1, API integration has many advantages over GUI and matches our requirements. A few more reasons for selecting API over GUI are listed:

1. Due to the existence of predetermined prompts, we have constructed a dictionary that enables us to build dialogues rapidly using the API. However, accomplishing the same task in a graphical user interface (GUI) would be considerably more time-consuming as it would require manual effort.
2. The objective is to create approximately 1000 dialogues that address the five dysfunctions

of teamwork, along with their corresponding levels (high, medium, and low). The API successfully generated a variety of dialogues without any repetitions, whereas the GUI produced duplicate dialogues when attempting to generate ten diverse dialogues using a single prompt.

3. Results are exported in Google Spreadsheet, which is not possible in GUI. The Spreadsheet is then converted to a Comma Separated Value(CSV) format. This format is highly favourable for data manipulation, analysis, and modelling. The tabular structure allows for easy handling of the generated dialogues, enabling us to perform in-depth analysis, data cleaning, and preprocessing as needed. This structured format is invaluable when preparing the dataset for subsequent stages of our research, such as model training and evaluation.

4. By utilising the API, we can modify the versions of chatGPT models according to our acquired knowledge. After experimenting with many models, such as ChatGPT-4, which is primarily designed for text, image, and voice analysis, we ultimately utilised GPT3.5 Turbo. However, we found that ChatGPT-4 did not provide any further benefits for content production. According to the description, ChatGPT-3.5 Turbo is more adept at generating content and aligning with our needs. Furthermore, the expense of producing content in 3.5 Turbo is lower than that of GPT-4

5. With API, we can effortlessly produce a multitude of dialogues based on a predefined dictionary to generate a desired quantity of dialogues with a single command, thereby significantly expediting the process. The efficiency gained through automation was particularly advantageous, as the manual generation(chatGPT GUI) of a comparable number of dialogues proved exceedingly time-consuming. This automation increased data acquisition speed and ensured consistency and non-repeatability, enhancing the reliability of our dataset outcomes.

6. With API, we can set up the temperature (creativity in the content) based on our requirements, which is impossible in GUI; the temperature parameter allowed us to tailor the content generation process to suit our needs precisely. We use Temperature 0.2 to focus on the contents specified in dialogue; the higher the temperature, the more creative writing we can have. However, we want to restrict ChatGPT API to give output based on our designed

prompt, so we use 0.2 as the temperature.

5.2 An Overview of the Five Teamwork Dysfunctions

Lencioni's considers the dysfunctions to be interrelated, and presents them as a pyramid. Team dysfunctions affect the team's performance and effectiveness and hinder their ability to collaborate. The figure 5.1 shows the hierarchy of team dysfunctions, starting from the absence of trust and ending with inattention to results. Each dysfunction depends on the one below it (Lencioni, 2012).

Figure 5.1 Lencioni's Pyramid

(Lencioni, 2012)

An overview of each dysfunction is listed below:

5.2.1 Absence of Trust

The absence of trust is the base of Lencioni's pyramid. Team members who cannot be open and comfortable with each other, help each other, and share weaknesses and mistakes, will need more trust to work effectively together. It is the first thing the team members should focus on; if they can not trust each other, how can the team achieve results? It is the critical part of group work, which begins with trust. It is: ***invulnerability***, as explained in Lencioni's Model (Lencioni, 2012).

5.2.2 Fear of Conflict

The fear of conflict is the second phase of teamwork after the absence of trust. Teams who lack trust are more susceptible to a lack of open discussion and debating skills. They have open discussions in a passive way called "back channels", where each team member talks about others in the back instead of confronting him. They avoid problems with others and avoid problems which lead to nonconstructive conflict. It is the ***artificial harmony*** as defined in Lencioni's model (Lencioni, 2012).

5.2.3 Lack of Commitment

The lack of commitment is the third level after fear of conflict. It is the beginning of failure in making decisions, long discussions about the same thing without making any progress toward a clear target that leads to deciding and approving one thing. The ***ambiguity***, as defined in Lencioni's model, is evidence of a lack of commitment (Lencioni, 2012).

5.2.4 Avoidance of Accountability

The avoidance of accountability is the fourth dysfunction, which starts when the overall team objectives are missed because they hesitate to confront deviant peers' behaviour to avoid interpersonal discomfort, affecting overall work standards. It is the level of ***low standards*** that Lencioni exhibited in his model (Lencioni, 2012).

5.2.5 Inattention to Results

Inattention to results is the last dysfunction resulting from a team's failure to be accountable for mistakes and bad performance. Team members focus on their personal goals instead of the collective goals. Each member focuses on individual status, like enhancing positions to exist or survive, rather than achieving meaningful goals. The ***ego and status*** are its symptoms (Lencioni, 2012).

5.3 A methodology for generating dialogues exhibiting different dysfunctions.

Patrick Lencioni has not only shed light on the root causes of teamwork dysfunctions but also provided actionable solutions to address each one. The model he employs resembles a chain, where the breakdown of a single link can lead to the deterioration of teamwork. Another approach to understanding his model is to take the opposite, positive (High-performance team) approach(Lencioni, 2012).

This deeper understanding is essential to establish an accurate context for each dysfunction. The ChatGPT API facilitated the representation of these dysfunctions. It assigned varying degrees of intensity – High, medium, and low – mirroring their potential impact within a team dynamic and creating a robust and insightful collection of dialogues that authentically portrayed the five teamwork dysfunctions and their respective levels.

5.3.1 Overview

The selection of prompts should encapsulate diverse facets of teamwork scenarios and exhibit each dysfunction with the related level score. The prompts we created were derived from Lencioni's Model. By strategically designing prompts encompassing different aspects of teamwork dysfunctions and corresponding level scores (high, medium, and low), we aimed to generate dialogues that authentically represent the teamwork dynamics. We diversified the prompts to ensure we covered the five teamwork scopes and the attributes of effective and ineffective team exchanges. Each prompt aligned with each dysfunction and its corresponding level score to guide the model to generate dialogues that capture the degree of dysfunction within the framework of teamwork.

The model responded by simulating dialogues that accurately reflected the attributes associated with teamwork dysfunctions. In section 5.3.2, we explained the methodology for generating the prompts.

5.3.2 A methodology for generating prompts

Following is the methodology we employed to create the prompts and the targeted dialogues for optimal outcomes:

1. Establish Context with the chatGPT GUI

   We began by establishing the *Context* within Patrick Lencioni's model as the first stage in our approach. We needed to understand the five teamwork dysfunctions and their respective degrees of influence to facilitate our discourse generation. To ensure we were on the right track, we employed the ChatGPT GUI to establish the context and verify whether the generated dialogues accurately embodied the context of each dysfunction and its corresponding level. This essential validation was the preliminary step for our later adoption of the ChatGPT API.

2. Craft Dialogue Prompts

   We crafted prompts corresponding to Lencioni's paradigm while ensuring we had well-established the context. We carefully designed these prompts to elicit responses that vividly portrayed the manifestations of each dysfunction within a team.

3. Revise and Refine

   The continuous improvement was a vital component of our process. We conducted a thorough examination and improvement of our prompts to ensure that they accurately represented the fundamental nature of each dysfunction, hence promoting clarity and precision in the generated dialogues.

4. Analyze and Reflect

   After getting results from the ChatGPT API, we checked the dialogues, which allowed us to examine the intricacies and the minor differences present in each dialogue, deepening our understanding of the levels of dysfunctions.

5. Seek Feedback

   We actively solicited comments from researchers, enhancing our understanding and confirming the precision of our generated dialogues.

6. Iterate

   By utilising the comments and insights obtained, we improved our prompts, enriched the context, and iterated through the process multiple times, guaranteeing that the created dialogues closely adhered to Lencioni's model.

5.3.3 Prompts Categorisation: Three Levels of Prompts for Team Dynamics

Lencioni's assessment involves evaluating the presence and intensity of each of the five dysfunctions within a team. His assessment tool was a questionnaire in which team members evaluated their team's behaviour and attributes by responding to statements or questions. These statements are fundamental for team members to express their observations and contribute to a comprehensive assessment of their well-being and efficiency. The scores obtained from these assessments are categorised into three levels: High, Medium, and Low.

To cover the five teamwork dysfunctions mentioned above in teamwork dialogues, we classified the prompts into three categories: High, Medium, and Low. Categorising the prompts in that way resulted in the following:

1. Generating dialogues that map to the scores as indicated in the Lencioni model. For example, High scores should exhibit specific characteristics of high-performing teams, whereas low scores should show the manifestations of teamwork dysfunctions.
2. A comprehensive dataset for our research analysis and model training.

5.3.3.1 Low-High Level Scores Category

High scores in Lencioni's assessment typically indicate that the team performs well and exhibits characteristics associated with effective teamwork (effective collaboration). Low scores are a symptom of notable dysfunctions or difficulties in teamwork, indicating possible problems inside the group, as explained in 5.2.

Here, we list the statements outlined in Lencioni's model that provide valuable insights and distinguish each dysfunction from the other, particularly emphasising only the 'low' and 'high' manifestations (Lencioni, 2012).

1. Dysfunction 1: Absence of Trust

No.	High Performing Team	Low Performing Team
1	Admit weaknesses and mistakes	Conceal their weaknesses and mistakes from one another
2	Ask for help	Hesitate to ask for help or provide constructive feedback
3	Accept questions and input about their areas of responsibility	Hesitate to offer help outside their own areas of responsibility
4	Give one another the benefit of the doubt before arriving at a negative conclusion	Jump to conclusions about the intentions and aptitudes of others without attempting to clarify them
5	Take risks in offering feedback and assistance	Fail to recognize and tap into one another's skills and experiences
6	Appreciate and tap into one another's skills and experiences	Waste time and energy managing their behaviors for effect
7	Focus time and energy on important issues, not politics	Hold grudges
8	Offer and accept apologies without hesitation	Dread meetings and find reasons to avoid spending time together
9	Look forward to meetings and other opportunities to work as a group	

Table 5.1 Explanation Table of Dysfunction 1 (High Performing Team vs. Low Performing Team) (Lencioni, 2012)

The table 5.2 below outlines the prompts we used to generate the low-High level score dialogues from the first dysfunction, "Absence of Trust", relying on *The Explanation Table of the Absence of Trust dysfunction* 5.1, which clearly distinguished between the 'low' and 'high' levels.

No.	Low-Level Prompts	High-Level Prompts
1	Generate a dialogue in which team members conceal their weaknesses and mistakes from one another.	Generate a dialogue in which team members admit weaknesses and mistakes.
2	Generate a dialogue in which team members hesitate to ask for help or provide constructive feedback.	Generate a dialogue in which team members ask for help.
3	Generate a dialogue in which team members hesitate to offer help outside their areas of responsibility.	Generate a dialogue in which team members accept questions and input about their areas of responsibility.
4	Generate a dialogue in which team members jump to conclusions about the intentions and aptitudes of others without attempting to clarify them.	Generate a dialogue in which team members give one another the benefit of the doubt before arriving at a negative conclusion.
5	Generate a dialogue in which team members fail to recognise and tap into one another's skills and experiences.	Generate a dialogue in which team members take risks in offering feedback and assistance.
6	Generate dialogue in which team members waste time and energy managing their behaviours for effect.	Generate a dialogue in which team members appreciate and tap into one another's skills and experiences.
7	Generate a dialogue in which team members hold grudges.	Generate a dialogue where team members focus time and energy on important issues, not politics.
8	Generate a dialogue in which team members dread meetings and find reasons to avoid spending time together.	Generate a dialogue where team members offer and accept apologies without hesitation.
9		Generate a dialogue where team members look forward to meetings and other opportunities to work as a group.

Table 5.2 Low-High Level Trust Prompts

2. Dysfunction 2: Fear of Conflict

No.	High Performing Team	Low Performing Team
1	Have lively, interesting meetings.	Have boring meetings.
2	Extract and exploit the ideas of all team members.	Create environments where back-channel politics and personal attacks thrive.
3	Solve real problems quickly.	Ignore controversial topics that are critical to team success.
4	Minimize politics	Fail to tap into all the opinions and perspectives of team members.
5	Put critical topics on the table for discussion	Waste time and energy with posturing and interpersonal risk management.

Table 5.3 Explanation Table of Dysfunction 2 (High Performing Team vs. Low Performing Team) (Lencioni, 2012)

The table 5.4 below outlines the prompts we used to generate the low-level score dialogues from the second dysfunction, "Fear of Conflict", relying on *The Explanation Table of the Fear of Conflict dysfunction* 5.3, which clearly distinguished between the 'low' and 'high' levels.

No.	Low-Level Prompts	High-Level Prompts
1	Generate a dialogue where team members have boring meetings.	Generate a dialogue where team members have lively, interesting meetings.
2	Generate a dialogue where team members create environments where back-channel politics and personal attacks thrive.	Generate a dialogue where team members extract and exploit the ideas of all team members.
3	Generate a dialogue where team members ignore controversial topics critical to team success.	Generate a dialogue where team members solve real problems quickly.
4	Generate a dialogue where team members fail to tap into all the opinions and perspectives of team members.	Generate a dialogue where team members minimise politics.
5	Generate a dialogue where team members waste time and energy with posturing and interpersonal risk management.	Generate a dialogue where team members put critical topics on the table for discussion.

Table 5.4 Low-High Level Conflict Prompts

3. Dysfunction 3: Lack of Commitment

No.	High Performing Team	Low Performing Team
1	Creates clarity around direction and priorities.	Creates ambiguity among the team about direction and priorities.
2	Aligns the entire team around common objectives.	Watches windows of opportunity close due to excessive analysis and unnecessary delay.
3	Develops an ability to learn from mistakes.	Breeds lack of confidence and fear of failure.
4	Takes advantage of opportunities before competitors do.	Revisits discussions and decisions again and again
5	Moves forward without hesitation.	Encourages second-guessing among team members.
6	Changes direction without hesitation or guilt.	

Table 5.5 Explanation Table of Dysfunction 3 (High Performing Team vs. Low Performing Team) (Lencioni, 2012)

The table 5.6 below outlines the prompts we used to generate the low-High level score dialogues from the third dysfunction, "Lack of Commitment", relying on *The Explanation Table of the Lack of Commitment dysfunction* 5.5, which clearly distinguished between the 'low' and 'high' levels.

No.	Low-Level Prompts	High-Level Prompts
1	Generate dialogue in which team members create ambiguity about direction and priorities	Generate dialogue in which team members create clarity around direction and priorities.
2	Generate dialogue in which team members watch windows of opportunity close due to excessive analysis and unnecessary delay.	Generate dialogue in which team members align the entire team around common objectives.
3	Generate dialogue in which team members breed a lack of confidence and fear of failure.	Generate dialogue in which team members develop an ability to learn from mistakes.
4	Generate dialogue in which team members revisit discussions and decisions again and again.	Generate dialogue in which team members take advantage of opportunities before competitors do.
5	Generate dialogue in which team members encourage second-guessing among team members.	Generate dialogue in which team members move forward without hesitation.
6		Generate dialogue in which team members change direction without hesitation or guilt.

Table 5.6 Low-High Level Commitment Prompts

4. Dysfunction 4: Avoidance of Accountability

No.	High Performing Team	Low Performing Team
1	Ensures that poor performers feel pressure to improve.	Creates resentment among team members who have different standards of performance.
2	Identifies potential problems quickly by questioning one another's approaches without hesitation.	Encourages mediocrity.
3	Establishes respect among team members who are held to the same high standards.	Misses deadlines and key deliverables.
4	Avoids excessive bureaucracy around performance management and corrective action.	Places an undue burden on the team leader as the sole source of discipline.

Table 5.7 Explanation Table of Dysfunction 4 (High Performing Team vs. Low Performing Team) (Lencioni, 2012)

The table 5.8 below outlines the prompts we used to generate the low-High level score dialogues from the Fourth dysfunction, "Avoidance of Accountability", relying on *The Explanation Table of the Avoidance of Accountability dysfunction* 5.7, which clearly distinguished between the 'low' and 'high' levels.

No.	Low-Level Prompts	High-Level Prompts
1	Generate a dialogue in which team members create resentment among team members who have different performance standards.	Generate a dialogue where team members ensure that poor performers feel pressure to improve.
2	Generate a dialogue in which team members encourage mediocrity.	Generate a dialogue where team members identify potential problems quickly by questioning one another's approaches without hesitation.
3	Generate a dialogue in which team members miss deadlines and key deliverables.	Generate a dialogue where team members establish respect among members held to the same high standards.
4	Generate a dialogue in which team members place an undue burden on the team leader as the sole source of discipline.	Generate a dialogue where team members avoid excessive bureaucracy around performance management and corrective action.

Table 5.8 Low-High Level Accountability Prompts

5. Dysfunction 5: Inattention to Results

No.	High Performing Team	Low Performing Team
1	Retains achievement-oriented employees.	Stagnates/fails to grow.
2	Minimizes individualistic behavior.	Rarely defeats competitors.
3	Enjoys success and suffers failure acutely.	Loses achievement-oriented employees.
4	Benefits from individuals who subjugate their own goals/interests for the good of the team	Encourages team members to focus on their own careers and individual goals.
5	Avoids distractions.	Is easily distracted.

Table 5.9 Explanation Table of Dysfunction 5 (High Performing Team vs. Low Performing Team) (Lencioni, 2012)

The table 5.10 below outlines the prompts we used to generate the low-High level score dialogues from the Fifth dysfunction, "Inattention to Results", relying on *The Explanation Table of the Inattention to Results dysfunction* 5.9, which clearly distinguished between the 'low' and 'high' levels.

No.	Low-Level Prompts	High-Level Prompts
1	Generate a dialogue in which team members retain achievement-oriented employees.	Generate a dialogue in which team members stagnate or fail to grow.
2	Generate a dialogue in which team members Minimise individualistic behaviour.	Generate a dialogue in which team members rarely defeat competitors.
3	Generate a dialogue in which team members enjoy success and suffer failure acutely.	Generate a dialogue in which team members lose achievement-oriented employees.
4	Generate a dialogue in which team members benefit from individuals who subjugate their own goals/interests for the team's good.	Generate a dialogue in which teams encourage team members to focus on their own careers and individual goals.
5	Generate a dialogue in which team members avoid distractions.	Generate a dialogue in which team members are easily distracted.

Table 5.10 Low-High Level Results Prompts

5.3.3.2 Medium Level Scores category

Lencioni's assessment categorises teams susceptible to the five dysfunctions into High, Medium, and low Scores. High scores indicate that teams are performing well, and low scores indicate teamwork faces challenges and dysfunctions in specific areas. The medium scores imply that the team performs well in some areas. However, they need help with difficulties that demand more concentration and improvement, but teamwork is generally moderately affected overall.

When considering the medium score category, the suitable method to design prompts to generate the medium scores is to construct contradiction prompts that contrast with the low and high scores. In that way, we have moderate dialogues that balance our dataset. Below are the prompts for generating each dysfunction's Medium level score dialogues.

1. Trust

    - Generate a dialogue in which team members admit weaknesses and mistakes but also conceal their weaknesses and mistakes from one another.
    - Generate a dialogue in which team members hesitate to ask for help or provide constructive feedback but also accept questions and input about their areas of responsibility.
    - Generate a dialogue in which team members Hesitate to ask for help or provide constructive feedback but also ask for assistance.
    - Generate a dialogue in which team members hesitate to offer help outside their areas of responsibility but also accept questions and input about their areas of responsibility.
    - Generate a dialogue in which team members Jump to conclusions about the intentions and aptitudes of others without attempting to clarify them but also give one another the benefit of the doubt before arriving at a negative conclusion.
    - Generate a dialogue in which team members fail to recognize and tap into one another's skills and experiences but also appreciate and tap into one another's skills and experiences.
    - Generate a dialogue in which team members waste time and energy managing their behaviours for effect but also focus time and energy on important issues, not politics.
    - Generate a dialogue in which team members hold grudges but also apologize and accept them without hesitation.
    - Generate a dialogue in which team members dread meetings and find reasons to avoid spending time together but also look forward to meetings and other opportunities to work as a group.

2. Conflict

    - Generate a dialogue where team members create environments where back-channel politics and personal attacks thrive but also extract and exploit the ideas of all team members.

- Generate a dialogue where team members have boring meetings, but at the same time, they have lively, interesting meetings.
- Generate a dialogue where team members ignore controversial topics that are critical to team success, but at the same time, they solve real problems quickly.
- Generate a dialogue where team members fail to tap into all the opinions and perspectives of team members, but also they minimize politics.
- Generate a dialogue where team members waste time and energy with posturing and interpersonal risk management but also put critical topics on the table for discussion.

3. Commitment

   - Generate a dialogue in which team members create ambiguity among the team about direction and priorities but also develop clarity around orientation and preferences.
   - Generate a dialogue in which team members watch windows of opportunity close due to excessive analysis and unnecessary delay but also align the entire team around common objectives.
   - Generate a dialogue in which team members breed a lack of confidence and fear of failure but also create an ability to learn from mistakes.
   - Generate a dialogue in which team members revisit discussions and decisions repeatedly but also move forward without hesitation.
   - Generate a dialogue in which team members encourage second-guessing among team members but also change direction without hesitation or guilt.

4. Accountability

   - Generate a dialogue where team members create resentment among team members with different performance standards, but at the same time, the team ensures that poor performers feel pressure to improve.
   - Generate a dialogue where team members encourage mediocrity but also identify potential problems quickly by questioning one another's approaches without hesitation.

- Generate a dialogue in which team members miss deadlines and key deliverables but also establish respect among team members who are held to the same high standards.
- Generate a dialogue in which team members place an undue burden on the team leader as the sole source of discipline but also avoid excessive bureaucracy around performance management and corrective action.
- Generate a dialogue in which team members may hesitate to confront one another about performance or behavioural issues, which will, in some cases, affect team results.

5. Results

- Generate a dialogue in which team members fail to grow but also retain achievement-oriented employees.
- Generate a dialogue in which team members rarely defeat competitors, but also they minimise individualistic behaviour.
- Generate a dialogue in which team members Lose achievement-oriented employees, but they also enjoy success and suffer failure acutely.
- Generate a dialogue in which team members are encouraged to focus on their own careers and individual goals. Still, they also benefit from individuals who subjugate their own goals for the team's good.
- Generate a dialogue in which team members are easily distracted, but also they avoid distractions.

5.4 Outcome

In our novel approach to creating the dialogue dataset, we selected the best model the chatGPT API offers. Lencioni identified 87 different cues that help assess a team's performance along the five dimensions, and we used 58 of those as prompts for ChatGPT, which leads us to acquire diverse dialogues that encompass different facets of teamwork dysfunctions and their associated level scores. For each dysfunction, we have around 200 dialogues that are comprised of 67 from each score level. The total number of all dialogues is 1000. Ultimately, we produced five distinct datasets, each comprising 200 dialogues. Diagram 5.2 illustrates the composition of the final 1000 dialogues across the five teamwork dysfunctions and their corresponding score levels.

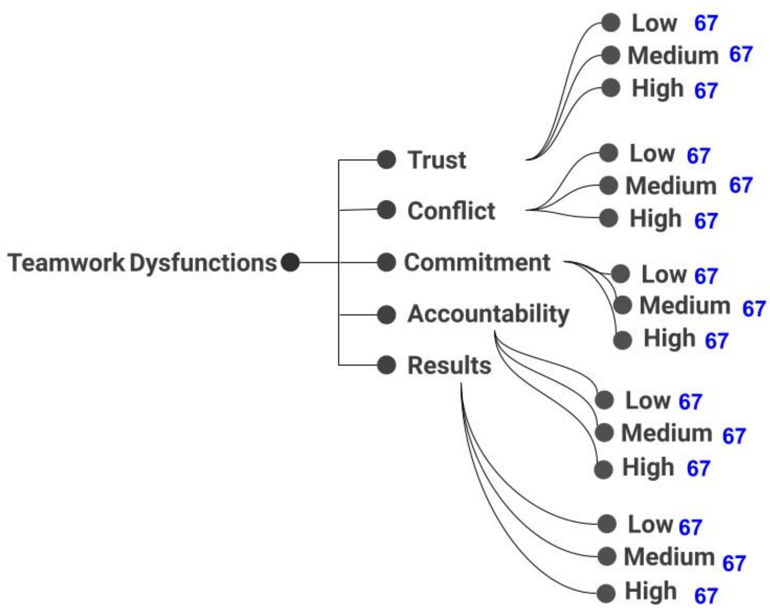

Figure 5.2 The Composition of the 1000 Dialogues

Here, we show samples for each dysfunction. **Note the Dialogue samples in appendix** "A".

Table 5.11 shows illustrative samples from the Trust dataset with the corresponding dysfunctions, representing the labels we need to train the machine learning model specifically designed to tackle issues connected to the first dysfunction, "Trust" 5.2.1.

No.	Dialogue	Dysfunction	Score	Label
1	A.1.1	Trust	Low	Trust Low
2	A.1.2	Trust	Medium	Trust Medium
3	A.1.3	Trust	High	Trust High

Table 5.11 Sample of the Trust dataset

Table 5.12 shows illustrative samples from the Conflict dataset with the corresponding dysfunctions, representing the labels we need to train the machine learning model specifically designed to tackle issues connected to the second dysfunction, "Conflict" 5.2.2.

No.	Dialogue	Dysfunction	Score	Label
1	A.2.1	Conflict	Low	Conflict Low
2	A.2.2	Conflict	Medium	Conflict Medium
3	A.2.3	Conflict	High	Conflict High

Table 5.12 Sample of the Conflict dataset

Table 5.13 shows illustrative samples from the Commitment dataset with the corresponding dysfunctions, representing the labels we need to train the machine learning model specifically designed to tackle issues connected to the third dysfunction, "Commitment" 5.2.3.

No.	Dialogue	Dysfunction	Score	Label
1	A.3.1	Commitment	Low	Commitment Low
2	A.3.2	Commitment	Medium	Commitment Medium
3	A.3.3	Commitment	High	Commitment High

Table 5.13 Sample of the Commitment dataset

Table 5.14 shows illustrative samples from the Accountability dataset with the corresponding dysfunctions, representing the labels we need to train the machine learning model specifically designed to tackle issues connected to the fourth dysfunction, "Accountability" 5.2.4.

No.	Dialogue	Dysfunction	Score	Label
1	A.4.1	Accountability	Low	Accountability Low
2	A.4.2	Accountability	Medium	Accountability Medium
3	A.4.3	Accountability	High	Accountability High

Table 5.14 Sample of the Accountability dataset

Table 5.15 shows illustrative samples from the Results dataset with the corresponding dysfunctions, representing the labels we need to train the machine learning model specifically designed to tackle issues connected to the last dysfunction, "Results" 5.2.5.

No.	Dialogue	Dysfunction	Score	Label
1	A.5.1	Results	Low	Results Low
2	A.5.2	Results	Medium	Results Medium
3	A.5.3	Results	High	Results High

Table 5.15 Sample of the Results dataset

5.5 Validation

5.5.1 Where are we?

Before we talk about validation, let us take a step back to position the generation of the dialogues within the objectives of the thesis.

Recall that the original objective of this thesis is to validate the hypothesis that the increase in student team dysfunctions during the pandemic was due to a mismatch between the communication needs of student team projects, and the social media apps used by students to coordinate teamwork, at the exclusion of any other communication medium–during the pandemic (see Chapter 2). We further hypothesized that different *work styles* have different communication needs (see Section 3.5), and that different *project types* required different *work styles* (Section 3.2).

Recall also that, to validate our hypotheses, we proposed to study a dataset of past problematic team projects, and to use traces of team communication exchanges to, 1) diagnose team dysfunctions, and 2) relate those dysfunctions to the combination $<$project type, social media app$>$, to see if there is any correlation–hence validating our initial hypothesis.

Recall further that, for the purposes of diagnosing team dysfunctions, we needed to: 1) identify what those dysfunctions were (see Section 5.2), and 2) develop automated tools that use NLP/sentiment analysis techniques to detect signs of these dysfunctions in existing dialogues. Recall also that we chose to use a *supervised learning approach* for dysfunction identification/detection, whereby we train a machine learning model with a data set of dialogues, labelled with team dysfunctions, that we later use to analyse traces of communication exchanges between team members (Chapter 2).

We first considered using the Enron dataset (Chapter 4) as the basis for model training. The Enron dataset consists of e-mail exchanges between Enron employees, supposed to reflect the corporate culture that eventually led to Enron's bankruptcy; because the Enron data set is *unlabeled*, we thought of using a zero-shot learning approach to train. As explained in Section 4.4, the dataset did not include *exchanges* per se, but mostly uni-directional email trails. Further, a preliminary experiment showed that there was no consensus as to the labelling of the different email trails.

All of the above led us to attempt to generate a labelled dataset automatically using ChatGPT. We explained in detail in this chapter how we went about generating 1000 dialogues, supposedly reflecting different performance (or dually, dysfunction) levels along Lencioni's five team performance dimensions (Section 5.2): (lack of) trust, embracing (fear of) creative conflict, (lack of) commitment, (avoidance of) accountability, and (lack of) attention to results.

The question we need to answer now before we can use it to train a machine learning model, is: *how good is this labelled dataset*? To this end, we need to evaluate it manually, i.e. by giving a sample of the 1000 dialogues to human subjects, and asking them to label the dialogues.

5.5.2 Validation Methodology

Here, we talk about how we would validate the labelling, *ideally*, i.e. if we had plenty of time and plenty of willing participants.

The things to watch out for:

- A representative data sample, for each of the five dysfunctions, and each of the three levels (low, medium, high)
- Dealing with 'Medium': how to set-up the experimental design to make sure that the medium level does not end up as a 'garbage bag'
- Check participants mutual agreement so that their collective judgement can be trusted

5.5.3 Preliminary experiment - experiment design

Validation is an essential step to ensure that the generated dialogues are of high quality and reliability and can be used to train machine learning models and improve the model's accuracy. The preliminary experiment aims to understand the complexity of the labelled dataset and test the generated dialogues to ensure that the labels are correctly assigned to the dialogues. By employing graduate students at the Master's level, we seek to achieve a high accuracy and consistency of dataset. The dialogue validation was performed as a hard(printed) copy and not by using online forms. We list below the approach, including the Participants as data annotators, dialogue and Prompt Selection, Labelling Guidelines, and Independent-Diverse Labelling.

- The Participants(Who are the participants)

  Our participants are fourteen master's students from the software engineering master's program. They are selected as data annotators for this experiment.

- Dialogue & Prompt Selection

  The total number of dialogue samples is 42, and the dialogues are from the Trust dataset. The dialogue samples were distributed as follows:

  - Some dialogue sets included only low and high and told the participants so
  - Some dialogue sets included low, medium, and high, and evoked the possibility of the three levels

  The total number of chosen prompts is 11 combined from the three-level scores distributed as follows:

  - Five prompts from the Low-level
  - Two prompts from the Medium-level
  - and Four prompts from the High-level

- Labelling Guidelines

  The course professor presented an orientation session to the participants to explain the experiment in general, the central concept of (Absence of)Trust dysfunction, the signs of the high-performing and low-performing teams, and the medium-level score to better understanding, ensure consistency in the data annotation process and decrease ambiguity.

- Independent-diverse labelling

  Each participant annotates the dialogues independently by giving each one three different dialogues.

5.5.4 Preliminary experiment - results

After collecting the results, We compared them to identify commonalities and differences with chatGPT API labels.

Table 5.16 shows the results attained from the validation.

Participants	**Dysfunction**	**ChatGPT Score**	**Participant Score**	**Number of Correct labels**
Participant 1	Trust	Low/ Low/ High/	High/ Low/ High/	2/3
Participant 2	Trust	Low/ Low/ High/	High/ High/ High/	1/3
Participant 3	Trust	Medium/ Low/ High/	High/ Low/ High/	2/3
Participant 4	Trust	Low/ Low/ High/	Low/ Low/ High/	3/3
Participant 5	Trust	Low/ Low/ High/	High/ Low/ Low/	1/3
Participant 6	Trust	Medium/ Low/ High/	High/ Low/ High/	2/3
Participant 7	Trust	Low/ Low/ High/	Low/ High/ High/	2/3
Participant 8	Trust	Medium/ Low/ High/	Medium/ High/ High/	2/3
Participant 9	Trust	Medium/ Low/ High/	High/ Medium/ High/	1/3
Participant 10	Trust	Low/ Low/ High/	High/ Low/ High/	2/3
Participant 11	Trust	Low/ Low/ High/	High/ Low/ Low/	1/3
Participant 12	Trust	Low/ Low/ High/	Low/ High/ Low	1/3
Participant 13	Trust	Low/ Low/ High/	High/ Low/ High/	2/3
Participant 14	Trust	Medium/ Low/ High/	High/ Low/ Medium	1/3

Table 5.16 Validation Results

We assigned numerical values for each level score. Low was assigned a value of 1, Medium was assigned a value of 2, and High was assigned a value of 3 to allow for quantitative analysis of participants' labels as shown in table 5.17.

Participants	D1 Score	Par Score	D2 Score	Par Score	D3 Score	Par Score
Participant 1	1	3	1	1	3	3
Participant 2	1	3	1	3	3	3
Participant 3	2	3	1	1	3	3
Participant 4	1	1	1	1	3	3
Participant 5	1	3	1	1	3	1
Participant 6	2	3	1	1	3	3
Participant 7	1	1	1	3	3	3
Participant 8	2	2	1	3	3	3
Participant 9	2	3	1	2	3	3
Participant 10	1	3	1	1	3	3
Participant 11	1	3	1	1	3	1
Participant 12	1	1	1	3	3	1
Participant 13	1	3	1	1	3	3
Participant 14	2	3	1	1	3	2

Table 5.17 Numerical Representation of the Scores

Here, we illustrate additional computations as listed in the tables below.

1. Average of the Correct Scores

Participants	Number of Correct Scores
Participant 1	2
Participant 2	1
Participant 3	2
Participant 4	3
Participant 5	1
Participant 6	2
Participant 7	2
Participant 8	2
Participant 9	1
Participant 10	2
Participant 11	1
Participant 12	1
Participant 13	2
Participant 14	1
Average of Correct Scores	23/42=0.55

Table 5.18 Average of the Number of Correct Scores

2. The agreement level for 'High': 10/14
3. The agreement level for 'medium': 1/14
4. The agreement level for 'low': 12/14
5. Cross-tabulation of the participant responses 5.19

	Student Score			
GPT Score	Low	Medium	High	Total
Low	12	1	10	23
Medium	0	1	4	5
High	3	1	10	14
Total	15	3	24	42

Table 5.19 Cross-tabulation of the participant responses

Many factors affecting the accuracy and reliability of the attained results can affect the manual validation process. We recognised considerable challenges during and after the validation process. We will illustrate them as follows:

1. **Annotation Guidelines:** We did not provide the students with a guidelines sheet with the validation sheet, which may affect the results because of the topic nature and may look ambiguous for the first time.

2. **Training Session:** We did not offer a training session that covered the subject matter(Trust). Well-trained participants are more likely to annotate better with consistent responses.

3. **Dialogue Length:** The dialogues in the validation sheet are multi-responses between more than two persons, considered not short dialogue. Achieving correct responses may be challenging at this point.

4. **Time Constraint:** Students needed more time to perform the validation because, as discussed before, they performed the validation after the mid-term exam, which lasted 3 hours, so they were exhausted and may need to focus better on the validation sheets and with about 15 minutes to finish the validation sheets.

5. **Validation Tool:** We used a Printed copy instead of an online form. Online forms could be more appropriate to maintain good results.

6. **Participant Expertise:** The domain's knowledge level affects the result's quality and accuracy. We may need experts in the field to gain better results.

7. **Language Constraint:** The Participants/students are native French speakers, and our validation sheets are in English. We assume this affects the overall results.

8. **Feedback and Iterative Process:** We did not give the students any feedback session about the validation results. Feedback influences the robustness and refining of the validation result over time.

5.6 Conclusion

The result signifies that approximately 54.76% of the dialogues were correctly labelled, leading us to the importance of understanding the reliability and effectiveness of our validation experiment. The factors discussed earlier provide insights for proposing future validation endeavours that will impact the overall outcome. Furthermore, future validation should include the rest of the datasets to achieve high accuracy while taking care of the mentioned manual verification process key factors. Perfection is an evolving target. We are committed to proceeding with model training even if we need to refine our validation experiment. Chapter 6 will explain what models we used and the accuracy of the results we attained.

CHAPTER 6
MODEL TRAINING FOR SENTIMENT ANALYSIS

This chapter mainly describes the workflow used for the model training. The primary objective of this thesis is to develop a model that can accurately classify/categorise Lencioni's five dysfunctions in group dynamics through the analysis of interpersonal dialogues (Aggarwal, 2023). This task aligns with the principles of supervised learning, where the models are trained on the labelled dataset to discern patterns and relationships between the provided features and the assigned dysfunction levels (Mahesh, 2020). Then, the model can predict the dysfunction level of new cases, offering a valuable mechanism for addressing teamwork dysfunctions. Four distinct machine-learning algorithms were used to train the model with the generated datasets. Support Vector Machine (SVM), Logistic Regression, Naïve Bayes, and Random Forest. These algorithms learn from labelled data to recognize patterns and make predictions on new, unseen data. An overview of each algorithm is presented in section 6.3.

6.1 Sentiment Analysis - An Introduction

Analyzing people's opinions, sentiments, valuations, opinions, attitudes, and feelings regarding goods, services, organizations, and so on is recognized as sentiment analysis, often known as opinion mining: people, problems, occasions, subjects, and characteristics. It stands for a vast issue space. Sentiment analysis, opinion extraction, gush mining, prejudice analysis, affect analysis, feeling analysis, and appraisal mining are only a few of the numerous terms and somewhat distinct tasks that exist. However, these days, opinion mining and sentiment analysis cover them all. Although opinion mining and sentiment analysis are often utilized in academia, sentiment analysis is more generally applied in industry. According to (Liu, 2012), it was Nasukawa and Yi who may have coined the phrase sentiment analysis in their 2003 paper (Nasukawa et Yi, 2003), while Dave, Lawrence, and Pennock (2003) may have been the first to identify opinion mining (Kushal, 2003). However, the literature on attitudes and beliefs was published earlier in 2001. Opinion mining and sentiment analysis are sometimes used synonymously. Specific phrases can also indicate sentiment, opinion, evaluation, and attitude. However, these ideas are different (Liu, 2012).

When it is necessary, we will tell them apart. The opinion itself still has a fairly wide connotation. Opinion mining and sentiment analysis mainly concentrate on viewpoints that convey good or negative feelings. Even though natural language processing (NLP) and linguistics have an extensive history, before 2000, only a few studies had been conducted on people's attitudes and opinions. The discipline has developed into a bustling area of research since then. That is due to several factors. Firstly, it has a vast array of uses in nearly every field. It should come as no surprise that sentiment analysis began and has proliferated simultaneously with social media. Social media studies are now targeting sentimental analysis. Since all of these fields are impacted by people's views, research in sentiment analysis has a significant influence on NLP and has the potential to significantly influence managing sciences, radical science, finances, and societal sciences (Liu, 2012)

6.1.1 Different Types of Analyses

Depending on the granularity of the prior study, there are several research issues with sentimental analysis. Sentiment analysis, conveniently enough, comes in three different levels:

6.1.1.0.1 Sentence Level

. The most detailed analysis of the document is the sentiment analysis at the sentence level. In this method, polarity is determined for each sentence since each sentence is a distinct unit and is capable of expressing different opinions. Sentences can be categorized as positive, neutral, and negative based on the opinion of the words used. The perception of neutrality here typically implies the deficiency of a noticeable opinion. There are two classifications of a sentence: subjective and objective. The most factual and nonjudgmental type of sentence is a subjective sentence. A subjective sentence contains no verdict or outlook regarding the object and entity.

On the other hand, an objective sentence contains an opinion. For example, look at the sentence: Canada's economy mainly depends on natural resources. This sentence is a factual one and does not contain any sentimental opinion. On the other hand, the sentence describes an exceptional experience. It conveys opinions about the experience since the subjective sentence should not be used as an index in deciding the polarity of the opinion.

6.1.1.0.2 Paragraph Level

. A frequency-based strategy was used in 2006. The terms that were found were referred to by the writers as essential subjects. Moreover, their approach used the TF-IDF technique, considering paragraph-level keywords. It was used to select a vital preparation of sentences. Sentences conveyed in individual sentences and their context inside the paragraph are considered when analyzing the overall sentiment expressed within a paragraph. This process is known as paragraph-level sentiment analysis. This analysis stage may entail determining the prevailing feeling or sentiments stated within the paragraph to communicate the sentiment the paragraph's collective content tries to represent. This may consider several verbal indicators at the paragraph level, including tone, context, and sentence structure, to ensure the overall mood expressed. Paragraph level can also necessitate determining the main themes or subjects covered in the paragraph and evaluating the feelings connected to each theme. It usually provides a clear understanding of the more significant material of the text (Liu, 2012).

6.1.1.0.3 Document Level

. This is the most basic type of classification. The whole subjective text is regarded as a fundamental item of information. In this analysis, the document is considered to contain opinions regarding a single object or entity. This method is inefficient if the document contains opinions about many objects, as in blogs. The entire document is classified as positive or negative. The sentences which are unnecessary and irrelevant are removed before dispensation. There is also a training dataset available. The system uses one widely used classification algorithm to classify the text based on the training data. In an unsupervised approach, the sentimental orientation(SO) of opinions text in a document is ascertained. The document is categorized as positive if the SO of these terms is positive; otherwise, it is negative. Document-level sentiment analysis can be done using machine learning algorithms, lexicon-based approaches, deep learning models, and rule-based systems. Businesses may learn important things about the general sentiment of textual data through document-level sentiment analysis (Liu, 2012).

6.1.2 Types of Information from the Text

Sentiment analysis techniques can be used to extract different types of information from text: polarity, polarity related to specific aspects, and opinions. They will be discussed, in turn.

6.1.2.0.1 Polarity

. This is the most basic information: it denotes whether the phrase shows a negative, positive, or unbiased sentiment. Polarity aids in identifying the general idea or direction the adverb-verb pair wishes to express. Mixed polarity is a condition when there are contradictory sentiments and instructions within a phrase. For example, the phrases "run quickly" and "quickly" suggest a positive sentiment (speed), while "run" is neutral. This creates a mix of positive and neutral sentiments within the phrase. When a verb of the "propagation" and "transfer" type is employed in an expression or sentence, and it is necessary to ascertain the sentiment of an argument that has previously been neutrally polarized, the decree of propagation is applied, for example, the verb phrase "to admire" (which implies a positive sentiment) influences the sentiment of "his behaviour" to be positive. Therefore, the sentiment of "his behaviour" is determined as positive due to the influence of the verb "to admire." Another example states, "Mr. X" is associated with the action of "supports" and the concept of "crime business," which is negative. This combination leads to the sentiment of "Mr. X" being determined as negative, as the negative sentiment associated with "crime business" is transferred to "Mr. X" due to his support for it(Liu, 2012, p. 66).

Dominant polarity depends on the various rules. When the polarities of a verb and an entity in a sentence point in opposing commands, the polarity of the verb is dominant. This composition rule suggests that when a negative sentiment ("to deceive") is associated with a positive sentiment ("hopes"), the resulting sentiment of the phrase "to deceive hopes" remains negative. The negative sentiment of "to deceive" outweighs or overrides the positive sentiment of "hopes," resulting in an overall negative sentiment for the phrase "to deceive hopes." The approach characteristics of the phrase that comes after the coordinate connector, and, or but in a compound phrase, are dominant. The composition rule here indicates that despite the initial negative sentiment conveyed by the difficulty of climbing a mountain all night ("It was hard to climb a mountain all night long"), the subsequent positive sentiment introduced by the splendid view that rewarded the explorer at dawn ("a magnificent view rewarded the traveller at the morning") overrides the initial negativity. As a result, the overall sentiment of the entire sentence is determined as positive. Understanding polarity aids sentiment analysis; mixed polarity arises from contradictory sentiments within a phrase. Dominant polarity determines prevailing sentiment in conflicting situations, facilitating a nuanced understanding of emotional tone. These concepts assist analysts and readers in deciphering the intended meaning and emotional impact of written communication (Liu, 2012, p. 67).

6.1.2.0.2 Aspect-Based

. Opinion text classification at the sentence or document stage is sometimes inadequate for applications as it does not recognize opinion targets or attribute feelings to them. A document expressing a good view of an individual does not necessarily indicate that the author feels the same way about all of the entity's features, even if we presume each document analyzes a solitary entity. Similarly, a negative opinion piece does not always indicate that its writer is pessimistic about everything. We must identify the elements and ascertain if the feeling is satisfactory or unfavourable for each aspect to conduct a more thorough examination. To find such details, we target the aspect level. The entity and its qualities comprise the opinion target. In the outcome, the entity itself is represented by the GENERAL aspect. Aspect-based sentiment analysis so takes into account both aspects and entities.

Furthermore, it presents issues that demand more progressive NLP skills and yield various outcomes. Aspect extraction pulls out the assessed aspects. For example, the attribute "voice quality" of the thing "this phone" represents is present inside the statement, "The voice quality of this phone is amazing." Because the assessment is just concentrated on the phone's voice quality and not the phone as a complete, it should be noted that "this phone" does not point out the element GENERAL here (Liu, 2012, p.58)

The statement "I love this phone" measures the phone as its whole, that is, the GENERAL quality of the thing that "this phone" represents. Remember that whenever we discuss it, we need to identify the entity to which an element refers. We frequently leave out the entity in our explanation below to keep things simple. Aspect sentiment classification ascertains the polarity of the sentiments on various aspects—positive, negative, or neutral. The above sample receives favourable feedback regarding the "voice quality" element. The sentiment on the GENERAL element is also satisfactory in the second (Liu, 2012, p.59)

6.1.2.0.3 Opinion Mining

An idea that suggests a good or negative attitude is expressed by an opinion rule. Simple examples are individual feeling words and their underlying sentiments or complex phrases whose orientations may require subject expertise or common sense to decipher. A few of these rules are explained in this section. Compositional semantics, which holds that the significance of a compound statement is an occupation of its elements and the syntactic rules by which they are joined, is one approach to conveying these rules. Since many of these principles might be presented in several ways and can be domain and sentence-specific, the rules are described conceptually rather than considering how they can be articulated in real sentences. Depending on the situation. The study of compositional semantics from the sentiment analysis perspective is then discussed at the expression level to combine many input component expressions to provide a complete sentiment direction for the compound expression. A formalism like the BNF form is used to present the rules.

Positive ::= P

PO

Sentiment shifter N

Sentiment shifter NE

Negative ::= N

NE

Sentiment shifter P

Sentiment shifter PO

Two different positive emotion expressions are represented by the non-terminals P and PO. P stands for a single positive expression, such as a word or expression, and PO stands for a positive expression of several words (Liu, 2012, p.62)

Likewise, the non-terminals N and NE symbolize two categories of negative emotion expressions. Understanding that they are in a pseudo-language that states certain abstract notions rather than in the genuine BNF form is essential. It is challenging to identify them precisely because the sentiment shifter can take on a variety of shapes in a phrase and can come before or after N, NE, P, or PO. There could be words between the emotion shifter and the positive (or negative) sentiment expressions.

The ultimate feelings employed to ascertain the viewpoints on the objectives or components of a statement are POSITIVE and NEGATIVE. Negative Sentiment shifters, such as not, never, none, nobody, nowhere, neither, and cannot, are most often used. Another type of auxiliary verb is a modal verb, such as would, should, could, could, must, and ought. For instance, "The brake could be improved," which occasionally alters sentiment direction. One such sort of thing is presupposition. As may be seen by contrasting "It works" with "It hardly works," this situation is frequent for adverbs like barely and hardly. "Works" denotes a good thing, while "hardly works" does not since it implies that improvement was anticipated. Words that act similarly include "fail," "omit," and "neglect," as in, "This camera fails to impress me. Sarcasm also frequently reverses orientations; for example, "What a great car, it failed to start the first day." While identifying such shifts by hand would not be difficult, locating and managing. It is difficult for an automated system to phrase them accurately in real phrases. They also feature comparison viewpoints, so we provide them individually(Liu, 2012, p.63). The meekest and most widely used category is emotional words or phrases, which can indicate positive or negative opinions about certain characteristics.

6.1.3 Different Analysis Techniques

Different analysis techniques have been used, depending on the type of information to be extracted, but also reflecting advances in the field: lexicon-based, machine-learning based, and rule-based techniques. They will be discussed briefly in turn.

6.1.3.0.1 Lexicon-based techniques

Sentiment analysis relies on expressions expressing positive or bad feelings. Sentimentality words are sometimes called *opinion-bearing* or *polar* words in the study literature. Words with positive connotations are used to convey specific desired attributes or conditions, whereas words with negative connotations are used to convey certain undesirable attributes or conditions. Words that evoke good feelings include 'astounding', 'great', and 'gorgeous'. Words with negative connotations include 'horrible', 'terrible', and 'lousy'. In addition to single words, there are idioms and sentimental phrases, such as 'cost [someone] an arm and a leg.' When taken as a whole, they are called sentiment lexicon. Moving forward, we will refer to both words and phrases as *sentiment words* for simplicity in the presentation. Base and comparative types are the categories into which sentiment words may be separated. The sample above words are all of the basic type. Comparative and superlative sentiment words express opinions in contrast and superlative forms. Better, worse, best, worst, and so forth are examples of such words; they are superlative and comparative versions of their basic adjectives or adverbs, such as excellent and terrible. In contrast to sentimental statements of the sordid type, feeling words of the absolute type, such as "Pepsi tastes better than Coke," convey a comparison opinion on many entities rather than a typical opinion on one. This statement does not mention whether one of the two beverages is superior. It simply states that Pepsi tastes better than Coke. Kamps presented a more advanced method, which based the sentiment analysis on a WordNet distance approach (Kamps *et al.*, 2004). The direction of a specific adjective, an alternative bootstrapping technique, was suggested using three seed sets: neutral, negative, and positive. The method operates on a directed, weighted semantic network in which the surrounding nodes are neither part of the seed-unbiased set nor synonyms or antonyms of verses in WordNet (Liu, 2012, p.91)

6.1.3.0.2 Machine learning techniques

. Various machine learning algorithms and techniques have been applied in sentiment analysis. In particular, supervised learning techniques, where we train a model on a dataset where each text sample is labeled with a specific sentiment (positive, negative, neutral), have had many applications. A good example of a supervised learning problem is opinion spam detection, which can be formulated as a classification problem with two classes, fake and non-fake. Common supervised learning algorithms used in sentiment analysis include Support Vector Machines (SVM), Naive Bayes, Decision Trees, and Random Forests.

The other machine learning method is unsupervised learning. In this approach, we do not have a labelled dataset; the model identifies patterns and groups similar textual data such as K-means clustering, grouping similar data points. The unsupervised method helps discover patterns, relationships, and structures within data without needing labelled examples. The choice of method depends on the specific needs and complexities of the analysis we have(Liu, 2012; Pathak et Rai, 2023).

6.1.3.0.3 Rule-Based Technique

These techniques involve the identification of particular keywords and their associated polarity or emotion (positive or negative), along with the use of patterns to identify the sentiment expressed in a text. In this case, the calculation of a sentiment score usually devolves into simple counting of the number of positive, negative and neutral words or phrases that occur in a text. Following this, the sentiment of the text can be calculated using these words and predefined or hardcoded rules and patterns. For example, rules can be created that detect good or bad words (or phrases) and evaluate the number of such words in the text. More weight may be assigned to specific words (or phrases) or the fact that they are repeated in the text, while others may only match precise phrases (Pathak et Rai, 2023).

6.2 Model Training Process

Our chosen approach was machine learning-based sentiment analysis, specifically using supervised learning techniques. The model is trained on five distinct labelled datasets; each dataset maps to one of Lencioni's dysfunctions, and the labels are the dysfunction scores: low, medium, and high. High scores indicate that the team performs well and exhibits effective teamwork characteristics. Low scores indicate dysfunctions or difficulties in teamwork, indicating possible problems inside the group. The medium scores imply that the team performs well in some areas. However, they need help with difficulties that demand more effort and improvement. In such cases, teamwork is usually moderately affected. An overview diagram of the sentiment analysis process is illustrated in figure 6.1

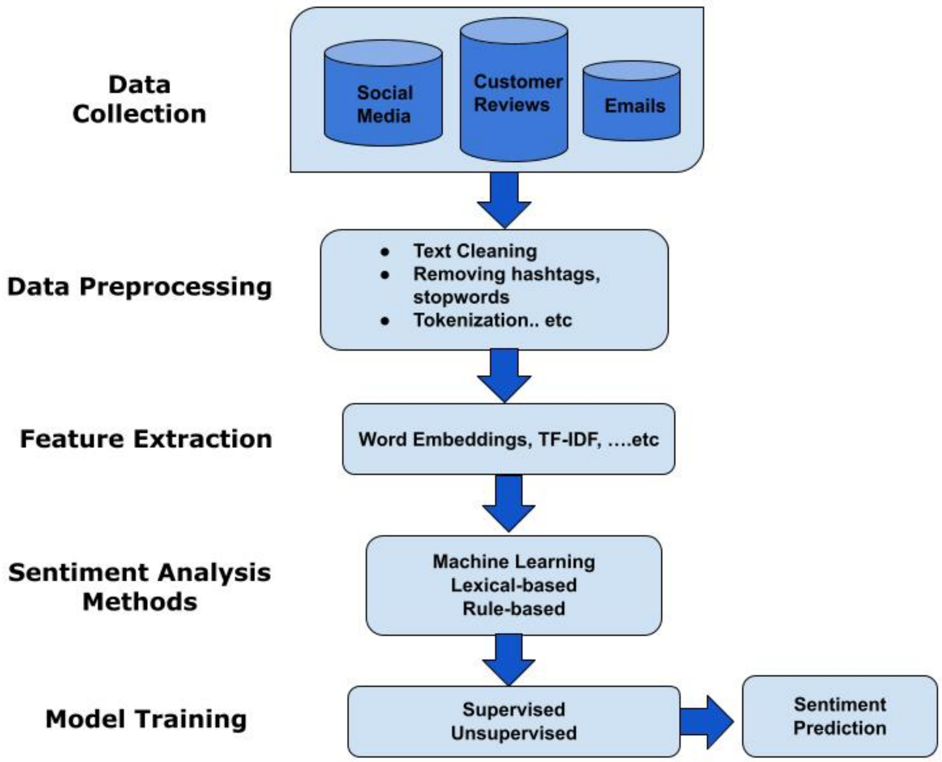

Figure 6.1 An overview diagram of the sentiment analysis process

Figure 6.2 shows the general workflow applied to the model's development.

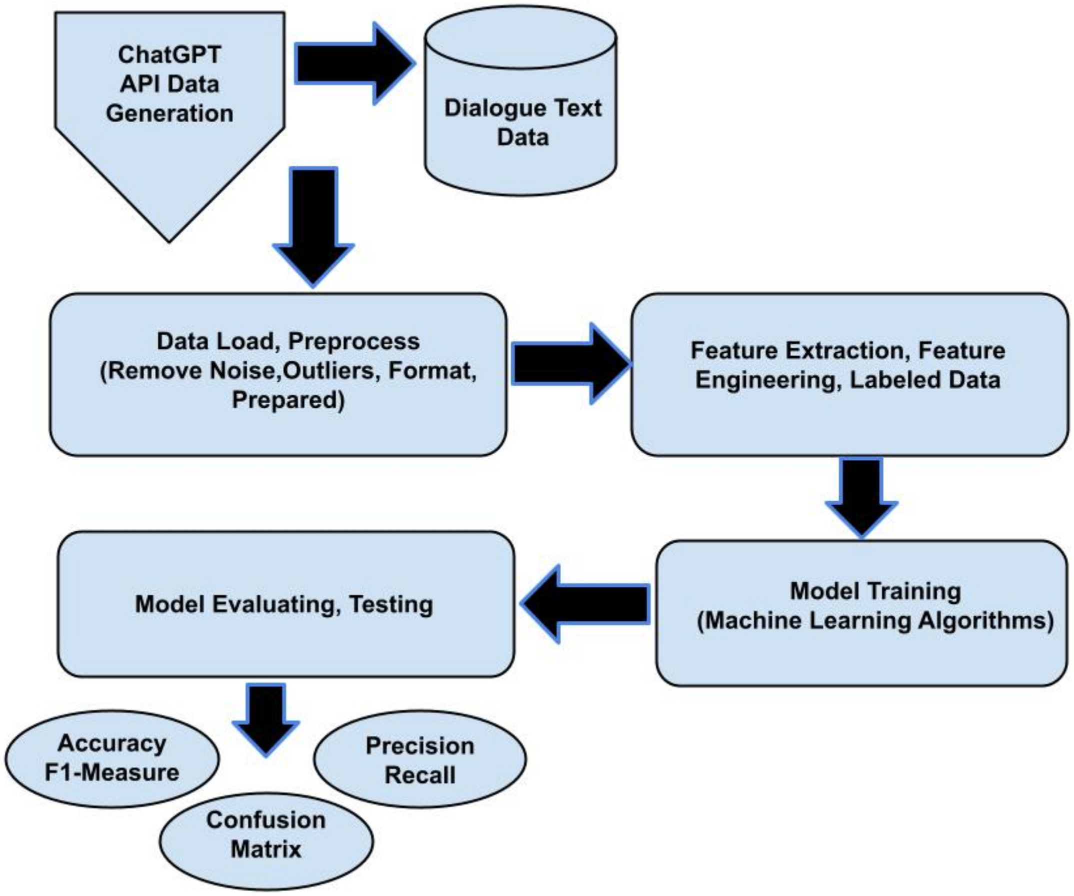

Figure 6.2 Model Development Process

We explain below the various steps:

6.2.1 Data Collection

Recall from chapter 4 that we could not find a dataset consisting of team dialogues that were labelled by team dysfunctions, and thus resorted to Open AI's ChatGPT to *generate our own dataset*. Indeed, for each team performance dimension/dysfunction, we used ChatGPT API (see 5), with the appropriate prompts, to generate dialogues between fictional team members, exhibiting different levels of performance/dysfunction for each dimension (see Section 5.3).

Our final dataset consisted of five distinct datasets, one for each teamwork dimension (Trust, Conflict, Commitment, Accountability, and Results). Each dataset contains 200 dialogues, divided evenly (about 67 dialogues each) between High, Medium, and Low. Recall that, in his work, Lencioni identified 87 different cues that help assess the performance of a team along the five dimensions, and we used 58 of those as prompts for ChatGPT (see Section 5.3.2). In the end, each prompt was used to generate between 7 and 10 dialogues, each. This ensured *diversity* in the data, which is needed to ensure the robustness of the trained model (Gong *et al.*, 2019).

6.2.2 Data Pre-Processing

Before feeding any machine-learning model with data, it is customary to pre-process the data to clean it for ingestion by our tool pipeline. This usually involves low-level data processing, such as removing empty lines, trailing blanks, capitalizing everything, removing (some) punctuation, etc.

6.2.3 Data Loading

The dataset is loaded using the pandas library. A powerful data manipulation library in Python. Our dataset consists of two columns, one for the dialogue itself, and the other for the class label (High, Medium, Low).

6.2.4 Label Encoding

The four algorithms that we chose to implement used numerical data. Thus, we had to translate (*encode*) the three labels (low, medium, high) into numerical values. We use the LabelEncoder from scikit-learn to encode the class labels.

6.2.5 Data Splitting

The dataset is split into training and testing sets to evaluate the model's performance. 80% of the data was used for training and 20% for testing, commonly called a "train-test split" (Géron et Bohy, 2019). The training set is used to train the model, while the testing set is kept separate and used to assess the model's performance on unseen dialogues. This step ensures that the model is able to identify teamwork dysfunctions, generalizes well to new dialogues, and is ready for real-world use.

6.2.6 Feature Extraction

We should transform our textual data (dialogues) into a numerical format that machine learning algorithms can process effectively (numerical feature vectors). Several approaches for converting textual dialogues into numerical feature vectors, known as feature extraction, such as Term Frequency-Inverse Document Frequency (TF-IDF), are widely used in natural language processing for converting text data into numerical format. TF measures the frequency of each word within a dialogue. Words that appear more frequently within a dialogue are assigned higher TF values. IDF measures the rarity of each word across all dialogues in the dataset. Words that are rare or unique to specific dialogues are assigned higher IDF values. Meanwhile, words common across many dialogues are assigned lower IDF values (Haddi *et al.*, 2013). By representing each dialogue as a vector of TF-IDF values corresponding to the importance of words in the corpus, the model can capture the unique linguistic patterns associated with each dysfunction's severity level.

6.2.7 Model training Overview

After performing all the necessary steps for data preparation, our dataset is ready to perform model training using the chosen machine learning algorithms. The dataset is considered small since it consists of 1000 dialogues, 200 for each dysfunction(67 from each level score). Traditional machine learning models function well in this situation; deep learning models such as recurrent neural networks (RNNs) or transformers would have been better if we had a large dataset. Accordingly, we chose Support Vector Machine, Logistic Regression, Naive Bayes, and Random Forest, described in Section 6.3, for reasons also explained in Section 6.3.

We used the above algorithms to identify the five teamwork dysfunctions with their corresponding level scores. The train_test_split, also known as a holdout, is a common technique in machine learning to train and evaluate machine learning models (Géron et Bohy, 2019). This technique splits the dataset into two parts: the training set, used for training the model, and the testing set, used to test the trained model. It is common, in the machine learning field, to break the data set into a 80 - 20, or 70 - 30 range. The train-test-split technique enables us to assess the performance of the trained model on unseen data, and helps detect *model overfitting*, wherethe machine learning model fails to generalize the results for new unseen data.

6.2.8 Model evaluation

We can measure how good a machine learning model is with different tests. There are assessment measurements that show how reliably it deals with new data it has not seen before. Example measurements for classification models include accuracy, precision, recall, and F1-score. Example measurements for regression models include *Mean Squared Error*(MSE), *Mean Absolute Error* (MAE), and R-square. Each metric has its purpose and reveals specific model aspects like correctness, reliability, and effectiveness(Colliot, 2023). We will discuss some metrics in some detail below.

6.2.8.1 Confusion Matrix

The confusion matrix provides detailed information about the model evaluation in the classification and covers all possible classes. It looks like a square matrix with actual target values compared to predicted ones. It shows the counts of true positives, true negatives, false positives, and false negatives. The confusion matrix, also known as an error matrix, allows us to measure accuracy, recall, and precision. In a binary classification case, the confusion matrix has two rows and two columns, as presented in figure 6.3 (Merouane *et al.*, 2022; Colliot, 2023). It divides the test samples into four categories based on their true and predicted labels:

- True Positives(TP): Instances correctly classified as positive by the model.
- True Negatives(TN): Instances correctly classified as negative by the model
- False Positives (FP): Instances incorrectly classified as positive by the model.
- False Negatives(FN): Instances incorrectly classified as negative by the model.

Figure 6.3 shows an example of the 2x2 confusion matrix. The green diagonal represents correct predictions, and the pink diagonal indicates wrong predictions.

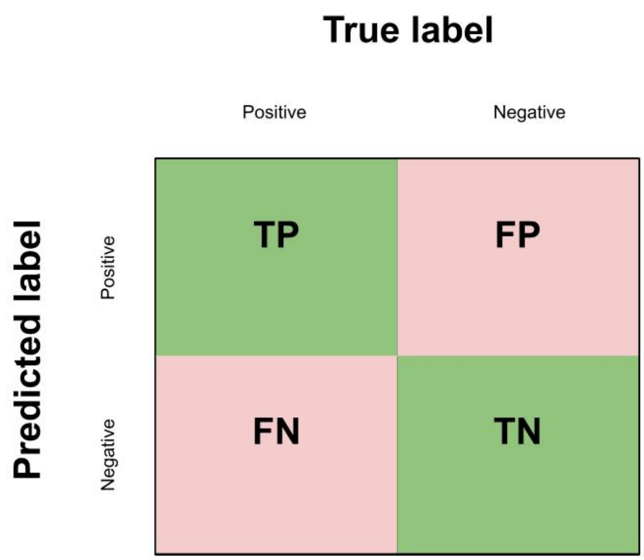

Figure 6.3 Confusion Matrix in the Case of Binary Classification

(Colliot, 2023)

In a multi-class classification case with N classes, the confusion matrix is an N×N matrix, as presented in figure 6.4. In this case:

- Each row corresponds to an actual class.
- Each column corresponds to a predicted class.
- Nij represents the count of instances where the true class is i and the predicted class is j
- The diagonal entries represent the counts of correct predictions.
- If the non-diagonal entries are equal to zero, there are no misclassifications between classes.

All performance measures can be easily computed using sklearn.metrics from scikit-learn, more details available at: `https://scikit-learn.org/stable/modules/model_evaluation.html#confusion-matrix`.

		Predicted			
Actual		C1	C2	......	C_n
	C1	N_{11}	N_{12}	......	N_{1n}
	C2	N_{21}	N_{22}	......	N_{2n}
	⋮	⋮	⋮	⋮	⋮
	C_n	N_{n1}	N_{n2}	......	N_{nn}

Figure 6.4 Confusion matrix for multi-class classification

(Tanha *et al.*, 2020)

6.2.8.2 Accuracy

Accuracy is a fraction of the instances that are classified correctly (Colliot, 2023).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{7}$$

6.2.8.3 Precision

Precision is a fraction of the positively classified instances that are indeed positive (Colliot, 2023)

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{8}$$

6.2.8.4 Recall

Recall or Sensitivity is a fraction of positive instances actually retrieved (Colliot, 2023).

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{9}$$

6.2.8.5 F1-score

F1-score is the harmonic mean of precision and recall (Colliot, 2023).

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{10}$$

6.2.8.6 Cross-Validation

Another technique for evaluating the model's performance on unseen data is cross-validation. In this technique, we split the dataset into subsets called "folds," using one of the folds as a validation set and the remaining folds for the training. The process is iterated several times, each utilising a different fold as the validation set. Ultimately, the results from every validation step are combined to get the mean value, which maximises the use of available data for both training and evaluation, resulting in a more reliable assessment of the model's effectiveness.

One commonly used cross-validation is K-fold cross-validation, which divides the dataset into k folds of equal size. Another cross-validation technique is *stratified cross-validation*, an enhanced version of K-fold cross-validation. It uses stratified sampling to generate folds that maintain a proportional representation of each class. During each iteration, the code generates a duplicate of the classifier, trains this duplicate using the training folds, and then uses it to make predictions on the test fold. Then, it counts the number of correct predictions and outputs the ratio of correct predictions (Géron et Bohy, 2019; Colliot, 2023). The average performance metric $\overline{M}$ across all folds is calculated using Equation 11.

$$\overline{M} = \frac{1}{k}\sum_{i=1}^{k} M_i \tag{11}$$

Where:

$\overline{M}$: Average performance metric across all folds

k : Number of folds in the cross-validation

M_i : Performance metric for the i-th fold

Figure 6.5 illustrates the k-fold cross-validation process (public wikipedia, 2024).

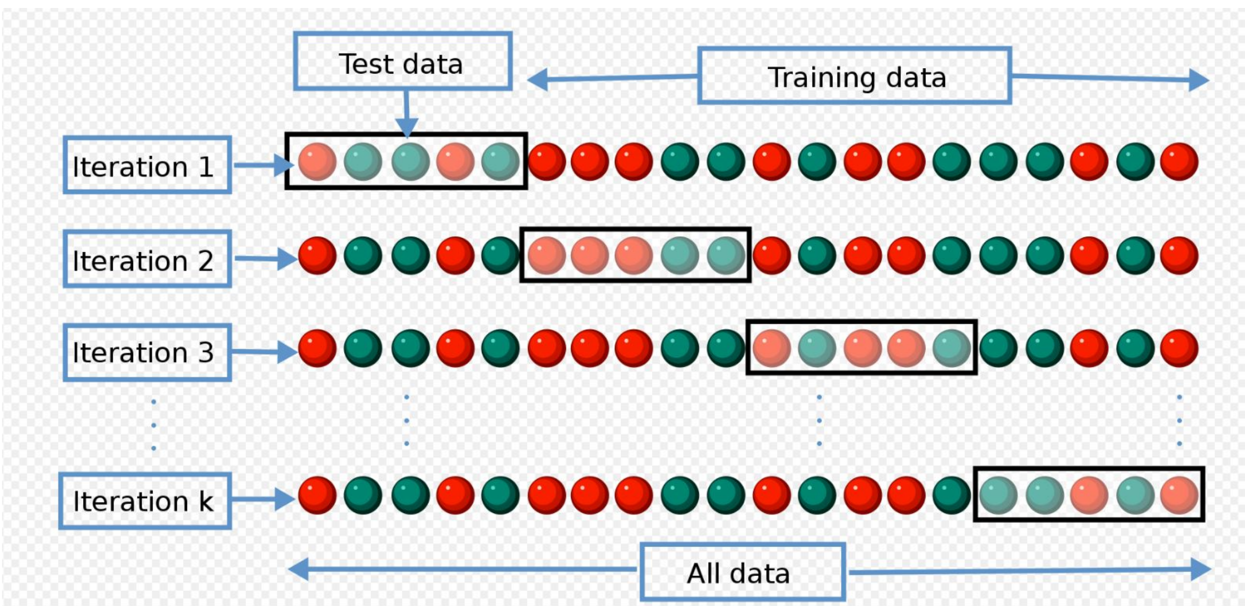

Figure 6.5 k-fold cross-validation

(public wikipedia, 2024)

We used multiple metrics, including accuracy, precision, recall, and F1-score, to evaluate the performance of the four models and their capabilities in accurately identifying teamwork dysfunctions. The obtained results are presented in tables in section 6.4.2. We also employed stratified k-fold cross-validation to evaluate each model's performance on the individual dysfunction dataset. In section 6.4.2.3, we present the mean accuracy of the stratified k-fold cross-validation for the five dysfunctions across the four models.

6.3 Algorithm Selection

Several factors influenced our choice of training algorithms. First, the dataset size (1000 dialogues) precludes the use of deep learning algorithms, whose number of parameters require very large datasets. Second, identifying team dysfunctions in team dialogues is a multi-class classification problem since we have five different team performance dimensions–and corresponding dysfunctions–and three different levels of performance/dysfunction for each dimension. Among the algorithms that perform well with small data sets and that support multi-class classification problems are *Support Vector Machines* (SVM), *Logistic Regression*, *Naïve Bayes*, and *Random Forest*. Finally, existing work on sentiment analysis and textual processing, in general, has shown these four algorithms perform best (Haddi *et al.*, 2013; Lei et Liu, 2021). Therefore, these are the algorithms that we will use in our experiments.

The second question that we needed to address was whether to train a single model to recognize all five dysfunctions, or one model per dysfunction? A number of reasons led us to choose the latter. Recall the way we obtained the data set (see Section 5.3). Recall that Lencioni identified, for each team performance dimension/dysfunction, several manifestations of that dysfunction (see Section 5.2), and that we used those manifestations as prompts to ChatGPT, to generate dialogues that exhibit the corresponding dysfunction. Finally, recall that we used the associated dysfunction as a *label* for the dialogue generated by ChatGPT. Consequently, each dialogue generated by ChatGPT had a single label. However, it is very conceivable that a dialogue generated by ChatGPT for a lack of trust dysfunction, for example, could exhibit other dysfunctions. In fact, according to Lencioni, it is even *probable* that a dialogue exhibiting one dysfunction would *also* exhibit others (Lencioni, 2012): indeed, he presented the team performance dimensions as a *pyramid*, where dysfunction at one level (for example trust), induces dysfunction at the next level (for example, fear of conflit).

In summary, the above reasons, we felt that it is best to train separate models, one for each dysfunction, to be trained with the dataset generated specifically for that dysfunction, because: 1) the dialogues had a single label each, by design, even though a dialogue may exhibit several dysfunctions, and 2) our hypothesis was that by having separate models, each model will focus on the salient features of the specific dysfunction of the corresponding dialogues. In this way, if we have a new dialogue, we submit it through the five trained models separately, each one assigning a score for a specific performance dimension/dysfunction, yielding five different labels for each dialogue, as in {Trust: High, (Healthy) Conflict: High, Commitment: Medium, Accountability: Medium, Attention to results: Low }.

In the remainder of this section, we present an overview of the four algorithms in turn. We were content to present the general ideas; interested readers can consult the many cited references that include further details about the algorithms hyper-parameters, exceptions, etc. The actual use of these algorithms on our data set is presented in Section 6.4, when we talk about the various parameters used, and present the actual performance metrics.

6.3.1 An Overview of Support Vector Machine (SVM)

SVM is a supervised machine learning algorithm mainly used for classification and regression problems. It deals with high-dimensional datasets. The algorithm's basic concept is to find a hyperplane that best divides data points into binary or multilabel classes (Géron et Bohy, 2019).

> The basic concept of the algorithm is to maximise the margin (i.e., the distance between the hyperplane and the closest inputs to the hyperplane)(Colliot, 2023).

Main Concepts of SVM

- **Hyperplane** The decision boundary that separates the two classes is the hyperplane. It is a line in two-dimensional spaces, and it becomes a hyperplane in higher dimensions.
- **Support Vectors** are the data points that lie closest to the hyperplane.

- **Margin** The margin is the distance between the hyperplane and the closest data support vectors.

Figure Shows the main concepts of SVM 6.6

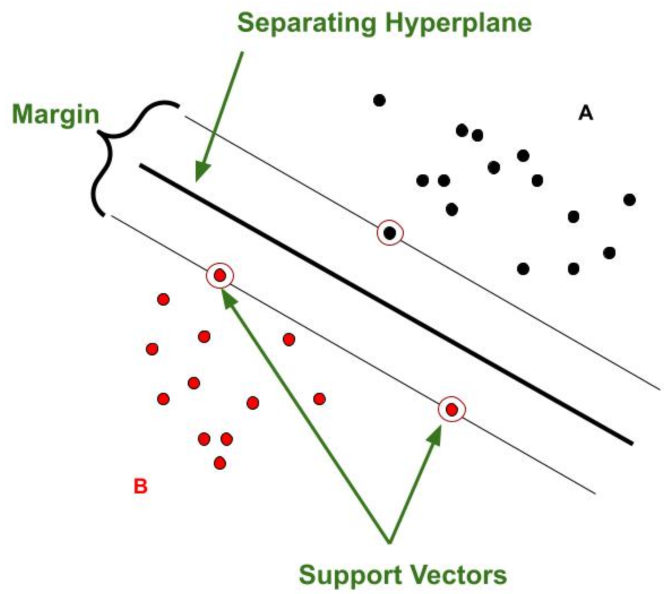

Figure 6.6 Support Vector Machine

6.3.1.1 Linear SVM Decision Function

Suppose we have two classes, A and B, and an infinite number of hyperplanes(lines) separate both classes. The SVM finds the hyperplane that maximizes the margin. The margin represents the distance between the hyperplane and the nearest data points of each class(support vectors). In this case, both classes are linearly separable because it is possible to draw a hyperplane that separates them without misclassification. Figure 6.7 shows Linearly separable SVM. The decision function of Linearly separable SVM is shown in equation 1

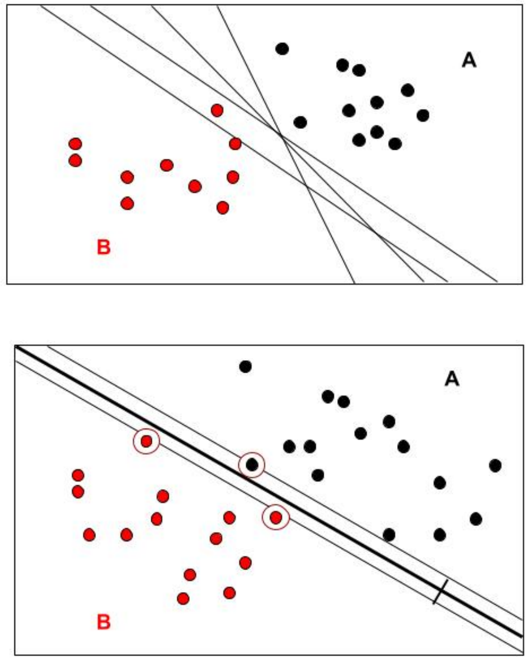

Figure 6.7 Support vector machine classifier in two-dimensional space

(Colliot, 2023, p. 43)

$$f(x) = w^T x + b \tag{1}$$

Where f(x) is the decision function that predicts the class label of the input vector, and w is the weight vector perpendicular to the hyperplane, and b is the bias term.

Margin Calculation The margin is inversely proportional to the norm of the weight vector

$$\text{Margin} = \frac{1}{\|\mathbf{w}\|}$$

Linear SVM Optimization Objective When the Decision function can not be strictly linearly separable, and the data point is on the wrong side of the decision boundary, misclassifications occur.

Hence, we need to maximize the margin. A larger margin leads to better generalization and better predictions.

$$\text{Minimize} \quad \frac{1}{2}\|\mathbf{w}\|^2 \quad \text{subject to} \quad y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \geq 1 \quad \text{for all} \quad i$$

Where x represents the feature vector, while y denotes the class label.

6.3.1.2 Non-Linear SVM Decision Function

Non-separable classes are those in which a straight line can not linearly separate the data points or where there is no hyperplane in the higher-dimensional space, and the classifier is called a Non-linear SVM classifier. In this case, SVM uses a technique called the kernel trick. Kernel functions allow SVM to implicitly map the input vectors into a higher-dimensional feature space(add more features, like polynomial features) where the data might become linearly separable. Several familiar kernel functions include linear, polynomial, radial basis function (RBF), and sigmoid kernels. The figure illustrates how adding a second feature (6.8) X2 will result in a linearly separable (Géron et Bohy, 2019). The equation (2) shows the decision function of non-linearly separable SVM's decision function (Colliot, 2023).

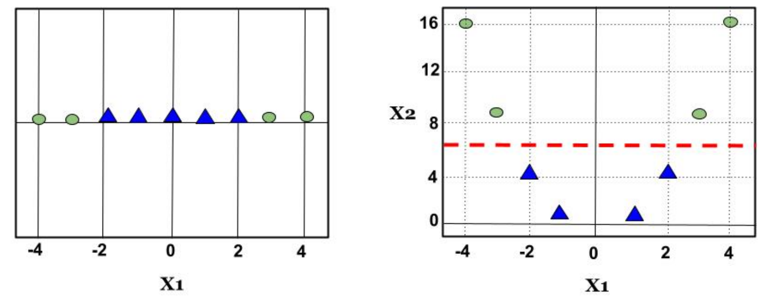

Figure 6.8 Using Kernel trick to make a dataset linearly separable

(Géron et Bohy, 2019, p. 149)

$$f(x) = w^T \phi(x) + b \tag{2}$$

Where:

- $f(x)$ is the decision function that predicts the class label of the input vector x.
- w is the weight vector in the transformed feature space.
- $\phi(x)$ is the feature mapping function that maps the input vector x into a higher-dimensional feature space.
- b is the bias term.

The decision function computes the dot product between the weight vector w and the feature vector $\phi(x)$ in the transformed feature space, and adds the bias term b to obtain the decision score. The sign of the decision score determines the predicted class label.

Common Kernel Functions

1. Polynomial kernel: $K(\mathbf{x}_i, \mathbf{x}) = (\mathbf{x}_i \cdot \mathbf{x} + c)^d$
2. Gaussian RBF kernel:
$$K_{\text{rbf}}(x, x_i) = \exp(-\gamma \|x - x_i\|^2)$$
3. Sigmoid kernel: $K(\mathbf{x}_i, \mathbf{x}) = \tanh(\alpha \mathbf{x}_i \cdot \mathbf{x} + c)$

The Gaussian RBF kernel is suitable when the data is not too large. It works well with text data, often exhibiting non-linear relationships between features and labels. RBF kernel works well in most cases. We chose the Gaussian radial Function.

6.3.2 An overview of Logistic Regression

The logistic regression model is a probabilistic linear model that transforms the signed distance to the hyperplane into a probability using the sigmoid function(Colliot, 2023)

The basic concept of the algorithm is finding the best hyperplane (line) that separates two classes. It is a predictive algorithm that uses independent variables to predict the dependent variable. It is similar to linear Regression, which is used to predict continuous outcomes, but with the difference that the dependent variable should be categorical. It is used for binary or multi-classification problems. In binary classification, the logistic function, known as the *sigmoid* function, maps any real-valued input to a value between 0 and 1, whereas in multi-classification problems, it uses the softmax function to compute the probabilities(Géron et Bohy, 2019).

6.3.2.1 Binary class logistic Regression

We calculate the conditional probability of the dependent variable Y, given the independent variable X. It can be written as: $P(Y = 1|X)$ or $P(Y = 0|X)$

$P(Y|X)$ is approximated as a sigmoid function applied to a linear combination of input features. The function maps any real value into another value between 0 and 1. In machine learning, we use sigmoid to map predictions to probabilities.

The probability of belonging to class 1 is given by equation 3. The logistic, also called the logit, noted $\sigma(\cdot)$, is a sigmoid function (S-shaped) that outputs a number between 0 and 1. It is defined in **Equation** 3 and **Figure** 6.9 shows the Logistic Regression.

$$\sigma(F(x)) = \frac{1}{1 + e^{-F(x)}} \tag{3}$$

- x represents the input features of an instance/input.

- $F(x)$ represents the linear combination of the input features x and their corresponding weights w. it is expressed as $F(x) = w_0 + w_1x_1 + w_2x_2 + \ldots + w_nx_n$, where w_0 is the bias term and $w_1, w_2, \ldots, w_n$ are the weights associated with each feature $x_1, x_2, \ldots, x_n$ respectively.

The sigmoid function $\sigma(\cdot)$ then takes the linear combination $F(x)$ as its argument and outputs a value between 0 and 1. This output represents the estimated probability that the instance belongs to a certain class, with 0 indicating a low probability and 1 indicating a high probability.

The **decision boundary** is a line or hyperplane that separates the instances belonging to class 0 and class 1. It is determined by the equation $\mathbf{w}^T\mathbf{x}+b = 0$. For example, we have two classes: spam and non-spam emails. We decide based on a predefined threshold value: if the predicted probability is closer to 1, it suggests a higher likelihood that the instance belongs to the spam class, and if it's closer to 0, it suggests a higher likelihood that it belongs to the non-spam class6.9. (Géron et Bohy, 2019).

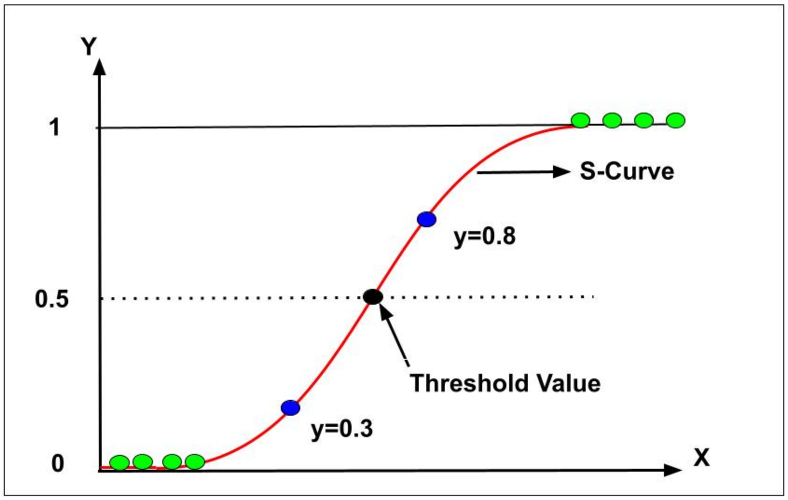

Figure 6.9 Overview of Logistic Regression

6.3.2.2 Multinomial Logistic Regression

The second type of logistic regression is the multinomial, which is used when we have more than two classes to predict by using the softmax function(also called the normalized exponential). the softmax function computes probabilities for each class, and the class with the highest probability value will be selected (Colliot, 2023). The **softmax function** is defined in equation 4.

$$P(y_i = C_k|\mathbf{x}_i) = \frac{\exp\left(\mathbf{w}_k^T \mathbf{x}_i\right)}{\sum_{j=1}^{C} \exp\left(\mathbf{w}_j^T \mathbf{x}_i\right)} \tag{4}$$

Where:

- $P(y_i = C_k|\mathbf{x}_i)$ is the probability that the i-th observation belongs to class C_k,
- $\mathbf{x}_i$ is the feature vector for the i-th observation,
- $\mathbf{w}_k$ is the weight vector corresponding to class C_k,
- C is the total number of classes.

Each class C_k is characterized by its own hyperplane $\mathbf{w}_k$. For a given input $\mathbf{x}$, we can compute the signed distance $\mathbf{x}^\top \mathbf{w}_k$ between the input $\mathbf{x}$ and the hyperplane $\mathbf{w}_k$. These signed distances are then transformed into probabilities using the softmax function (Colliot, 2023).

6.3.3 An Overview of Naïve Bayes

Naive Bayes is a method that considers initial beliefs about classes. It combines these prior probabilities with observed data to calculate each class's updated beliefs, called posterior probabilities. Then, choose the class with the highest posterior probability as the predicted class for a given instance. This approach allows Naive Bayes to predict using prior knowledge and observed evidence. A Naive Bayes classifier is a probability model that estimates class probability for feature sets. Bayes' theorem is its foundation. The model is "naive" because it assumes feature independence given the class label. The classifier learns from labelled data. It finds each feature's conditional probability per class. New instances are classified using the maximum posterior probability (Colliot, 2023). Gaussian Naive Bayes handles continuous features. Multinomial Naive Bayes deals with discrete features. Bernoulli Naive Bayes is for binary features (Mitchell, 1997). Equation 4 represents Bayes' theorem, a fundamental concept in probability theory.

$$P(h|D) = \frac{P(D|h) \cdot P(h)}{P(D)} \tag{4}$$

Where:

$P(h|D)$ is the posterior probability of hypothesis h occurring given that evidence D has been observed.

$P(D|h)$ is the likelihood or conditional probability of observing evidence D given that hypothesis h is true.

$P(h)$ is the prior probability of hypothesis h.

$P(D)$ is the probability of observing evidence D.

The theorem with the total probability is presented in Equation 5

$$P(D) = \sum_i P(D|h_i) \cdot P(h_i) \tag{5}$$

Where:

$P(D)$ is the probability of outcome D.

$P(D|h_i)$ is the probability of outcome D given hypothesis h_i.

$P(h_i)$ is the prior probability of hypothesis h_i.

The sum is taken over all possible hypotheses h_i.

In Naive Bayes classification, the goal is to predict the class label $\hat{h}$ for a given instance based on its observed features $\mathbf{D_1}, \mathbf{D_2}, ..., \mathbf{D_n}$. This prediction process involves computing the posterior probability of each class given the observed features and selecting the class with the highest probability as the predicted label.

The prediction process using the Naive Bayes classifier can be represented mathematically as in equation 6:

$$\hat{h} = \underset{h \in \mathcal{H}}{\text{argmax}}\, \Pi(P(h|D_1, D_2, ..., D_n)) \tag{6}$$

Where:

$\hat{h}$ is the predicted class label.

$\mathcal{H}$ denotes the set of all possible class labels.

$P(h|D_1, D_2, ..., D_n)$ is the posterior probability of class h given the observed features.

Π represents the projection operation that extracts the posterior probabilities.

More detailed information on Naive Bayes classification is available at: (scikit-learn developers, 2024)

6.3.4 An Overview of Random Forest

> "A random forest is an ensemble of decision trees with randomness introduced to build different trees"

(Colliot, 2023)

Random Forest combines the random selection of records with the random selection of attributes. This prevents the model from learning too much detail, giving the trees variety. When new data comes, all trees vote on the prediction. The combined vote makes Random Forest accurate and robust (Géron et Bohy, 2019; Colliot, 2023).

Main Concepts of Random Forest

- Decision Trees: The decision tree is one of the fundamentals applied here. These simple models divide the data into subsets with homogeneous features, thus choosing the most favourable training samples according to the target variable (the variable we are trying to predict). Split is done at each feature provided by the best separation of the criterion (impurity of Gini or information gain).
- Ensemble of Trees: The Random Forest combines a set of single decision trees. Each tree is built using a bootstrap of the data and a feature subset randomly extracted. Randomness is used as a decorrelation process that disconnects the trees from one another, thereby minimizing overfitting disease and boosting overall model robustness.
- Voting: Once the input data being classified has been presented, each tree in the forest predicts the class, and the class that gets the most votes from all the trees is the ultimate prediction.

FIGURE 6.10 presents an overview of the Random Forest Classifier's architecture.

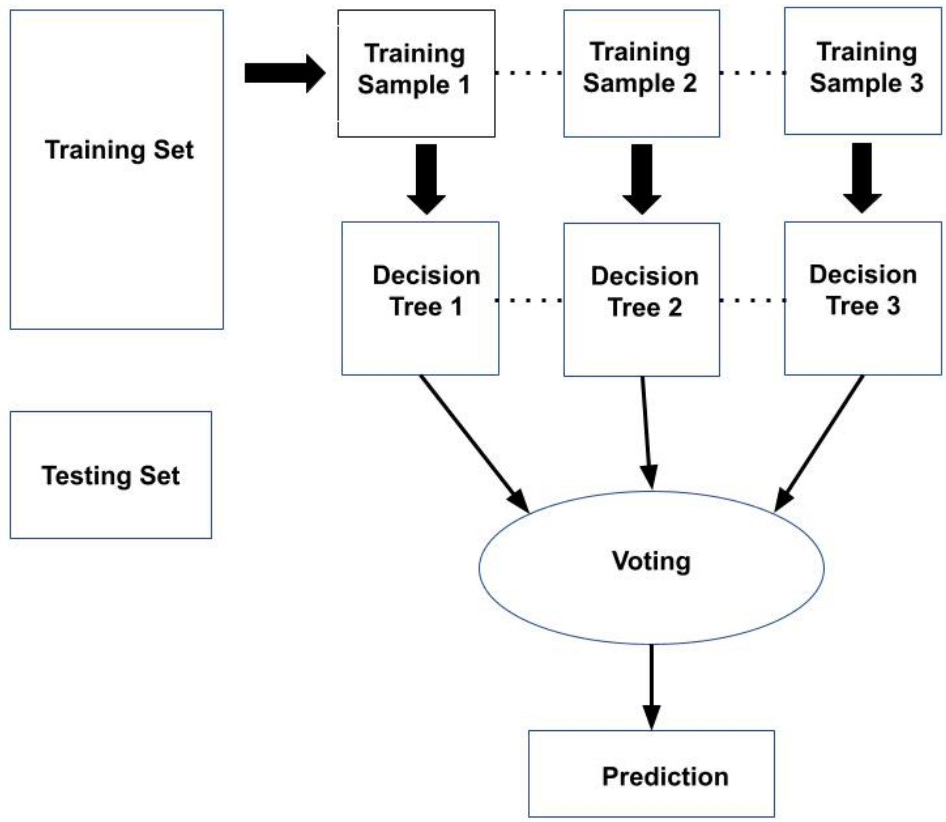

Figure 6.10 Overview of the Random Forest Classifier

(Le *et al.*, 2021)

6.4 Results

We trained each dataset for each dysfunction separately using Support Vector Machines, Logistic regression, Naive Bayes, and Random forest to enable us to identify each dysfunction with the corresponding level score(low, medium, high). Each dataset consists of 200 dialogues, comprising around $\approx$ 67 from each level score. This balanced dataset is important for training the models, as shown in figure 6.11. Every algorithm was calibrated with specific parameters, which were applied to achieve the best performance for its multi-class classification task. The performance of the four classification models has been evaluated based on their ability to classify the dialogues into three categories: low, medium, and high. We evaluated each model's results using several measures, such as accuracy, precision, recall, and f1-score, commonly used assessment measurements in classification models. Confusion matrices are created based on the dataset's actual and predicted labels to offer more detailed insights into our model performance. The obtained results for each dimension/dysfunction are shown in section 6.4.2.

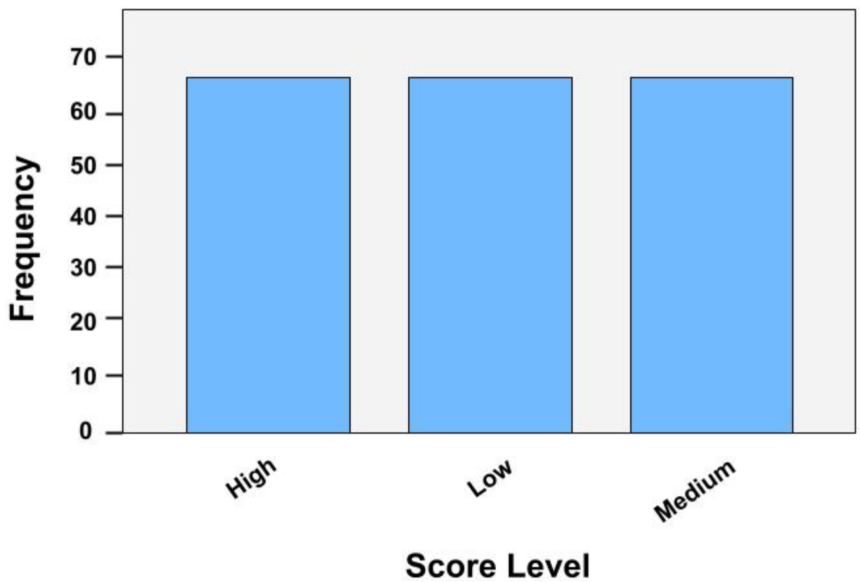

Figure 6.11 Distribution of Dialogues by Score

To judge our proposed model, we tried out several evaluation measures like accuracy, precision, recall, and f1-score and also plotted the confusion matrix visualizations as shown in section 6.4.2

6.4.1 Model training

We used the **scikit-learn** machine learning library to implement data preprocessing, model training, and evaluation. Following the training of these models, we computed their confusion matrices, which enabled us to measure their accuracy, precision, recall, and the F1-score. As well as Cross-validation. In the remainder of this section, we present some details about a) which variant of each of the four algorithms we used, and b) values for the main hyper-parameters, where applicable. The actual results are shown in Section 6.4.2.

6.4.1.1 SVM

The SVM model was built using the Radial Basis Function (RBF)/Gaussian kernel, and parameter C, which controls regularization, was initialized to 1.0. The RBF kernel was chosen because of its known ability to capture complicated relationships among high-dimensional data. It is also considered to be suitable when the data is not too large, which suits our 200 dialogues dataset. In addition, it works well with text data, often exhibiting non-linear relationships between features and labels.

The chosen value (1.0) for the regularization parameter (C) aims at finding a balance between the two goals of: a) obtaining a large classifier margin of separation, and b) and minimizing misclassification error. Such a strategy would normally result in greater overall performance of the learning classifier.

6.4.1.2 Logistic Regression

In the Logistic regression example, we set the model up with a maximum iteration of 1000. This value was deemed adequate to ensure that the algorithm converges to the right parameters with minimal time.

6.4.1.3 Naive Bayes Classifier

We employed the Multinomial Naive Bayes classifier. It entails specific parameters such as Laplace smoothing, known as alpha. Its default value is generally 1.0 to prevent zero probabilities.

6.4.1.4 Random Forest Classifier

In Random Forest, we employed 100 decision trees (estimators) in the ensemble to improve robustness and stability, hoping that it will give the model the ability to lessen the risk of overfitting while, at the same time, boosting the generalization capabilities when dealing with different data.

6.4.2 Results

In this section, we present the results obtained with the four algorithms used. We present the confusion matrices, from which we are able to compute the accuracy, precision, recall, and F1-score.

The results will be presented in three different ways:

1. *By algorithm*. We present the performance of each of the four algorithms on the five dysfunctions. This is presented in Section 6.4.2.1. In this case, we used the train_test_split methodology for testing. This presentation enables us to identify whether some dysfunctions are easier or more difficult to characterize than others.

2. *By dysfunction*. For each dysfunction, we compare the results of the four algorithms. This is presented in Section 6.4.2.2. This is just another view of the data presented in Section 6.4.2.1. It helps us identify which algorithm(s) perform significantly better or worse, for each dysfunction.

3. *The results of stratified K-fold cross-validation*. As explained in Section 6.2.8.6, the train_test_split technique used in Sections 6.4.2.1 and 6.4.2.2 yields reliable results when the test subset is selected randomly, which was the case. However, to get more reliable results, we use K-fold cross validation, which uses (K) different breakdowns of the dataset, between training

data and test data, and averages the results. When dealing with a multi-class classification problem, the *stratified* K-fold cross-validation ensures that each one of the K subsets is representative of the distribution of the classes in the full dataset. The results are shown in Section 6.4.2.3.

6.4.2.1 Results of the four Models

6.4.2.1.1 SVM

Dysfunction	**Accuracy**	**Precision**	**Recall**	**F1-score**
Trust	0.707	0.715	0.707	0.710
Conflict	0.83	0.90	0.83	0.83
Commitment	0.83	0.86	0.83	0.83
Accountability	0.95	0.96	0.95	0.95
Results	0.804	0.801	0.804	0.802

Table 6.1 Performance of the SVM Algorithm Across Different Dysfunctions

6.4.2.1.2 Logistic Regression

Dysfunction	**Accuracy**	**Precision**	**Recall**	**F1-score**
Trust	0.682	0.715	0.707	0.710
Conflict	0.78	0.86	0.78	0.77
Commitment	0.83	0.85	0.83	0.83
Accountability	0.83	0.83	0.83	0.824
Results	0.731	0.742	0.731	0.723

Table 6.2 Performance of Logistic Regression Algorithm Across Different Dysfunctions

6.4.2.1.3 Naive Bayes

Dysfunction	**Accuracy**	**Precision**	**Recall**	**F1-score**
Trust	0.537	0.523	0.537	0.483
Conflict	0.66	0.82	0.66	0.604
Commitment	0.78	0.82	0.78	0.78
Accountability	0.76	0.77	0.76	0.74
Results	0.609	0.634	0.609	0.612

Table 6.3 Performance of the Naive Bayes Algorithm Across Different Dysfunctions

6.4.2.1.4 Random Forest

Dysfunction	**Accuracy**	**Precision**	**Recall**	**F1-score**
Trust	0.756	0.767	0.756	0.753
Conflict	0.73	0.79	0.73	0.73
Commitment	0.804	0.851	0.804	0.804
Accountability	0.78	0.80	0.78	0.77
Results	0.707	0.709	0.707	0.700

Table 6.4 Performance of the Random Forest Algorithm Across Different Dysfunctions

6.4.2.2 Results of the five dysfunctions

Each table represents one dimension/dysfunction(Trust, Conflict, Commitment, Accountability, and Results). For each dimension, dialogues are classified into three level scores; for example, for Trust dysfunction, the dialogues are classified into Trust Low, Trust High, and Trust Medium. Our models assigned numerical values(0 for Low, 1 for Medium, and 2 for High) to indicate the severity/score level of each dialogue in the teamwork conversation.

6.4.2.2.1 The lack of trust dysfunction

Algorithm	Accuracy	Precision	Recall	F1-score
SVM	0.707	0.715	0.707	0.710
Logistic Regression	0.682	0.683	0.682	0.682
Naïve Bayes	0.537	0.523	0.537	0.483
Random Forest	0.756	0.767	0.756	0.753

Table 6.5 Results for the trust dysfunction

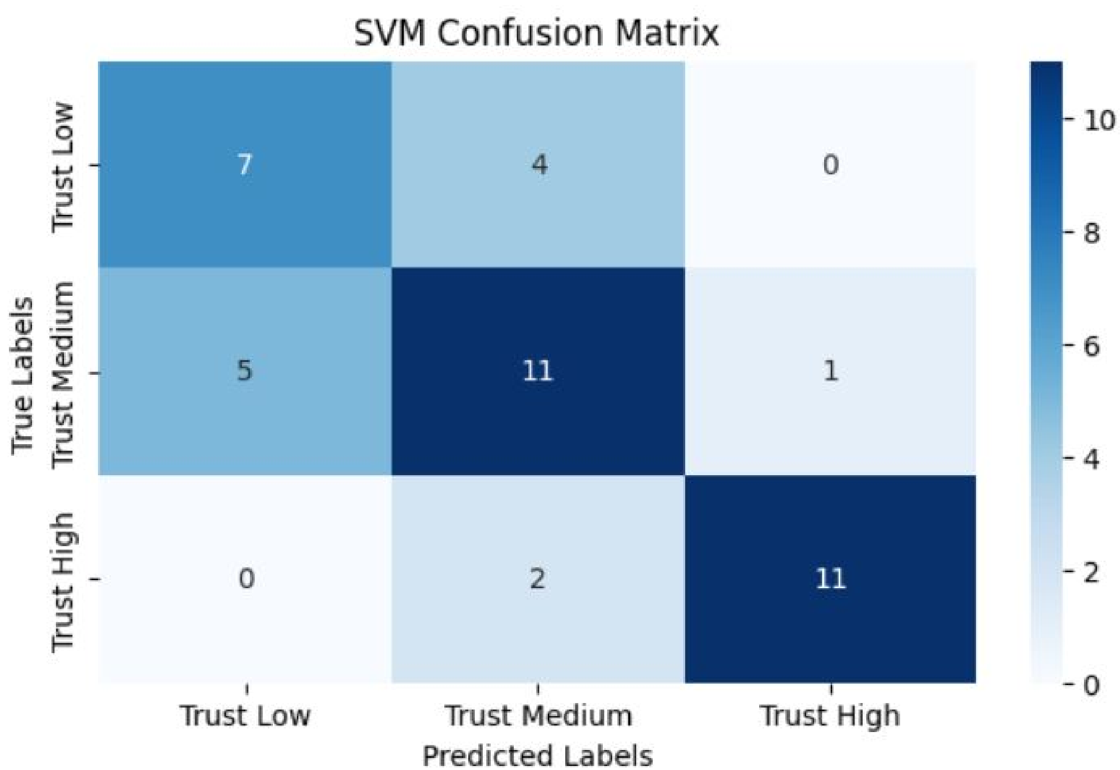

Figure 6.12 Confusion matrix of SVM

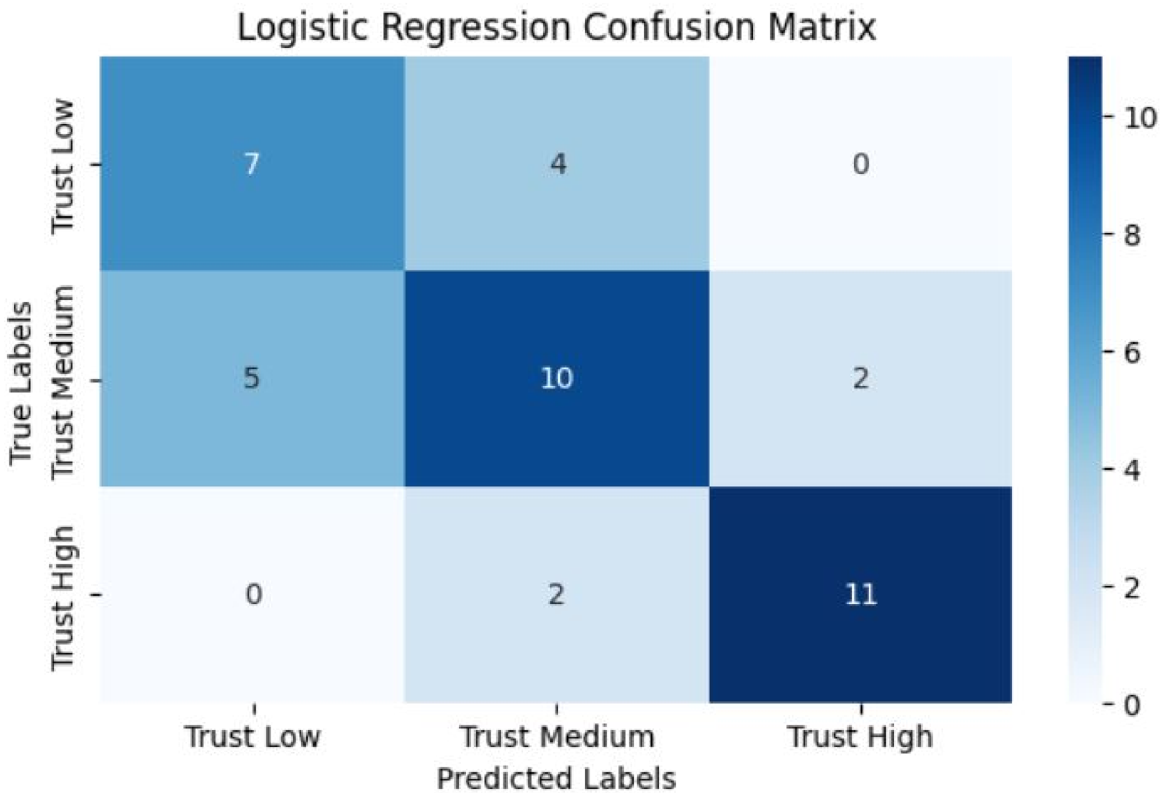

Figure 6.13 Confusion matrix of Logistic Regression

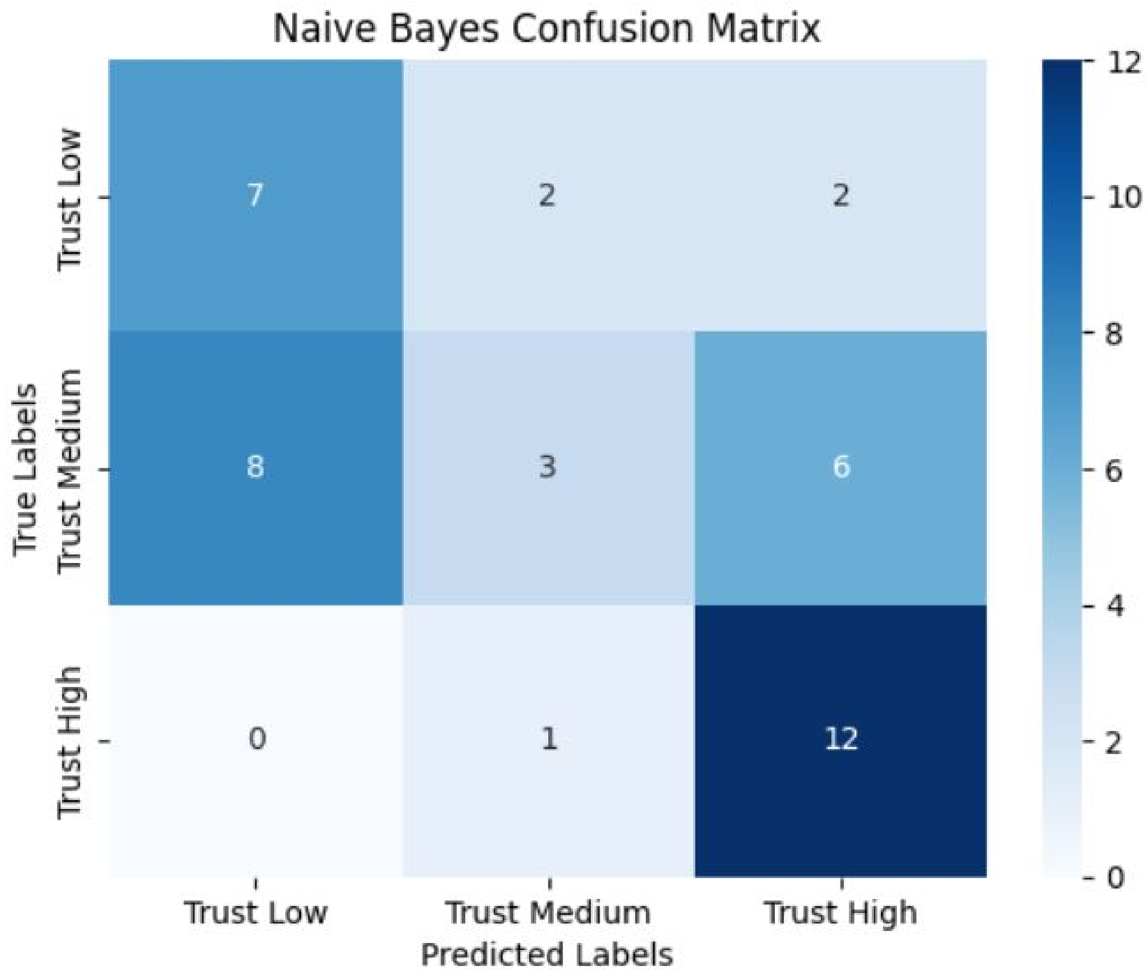

Figure 6.14 Confusion matrix of Naive Bayes

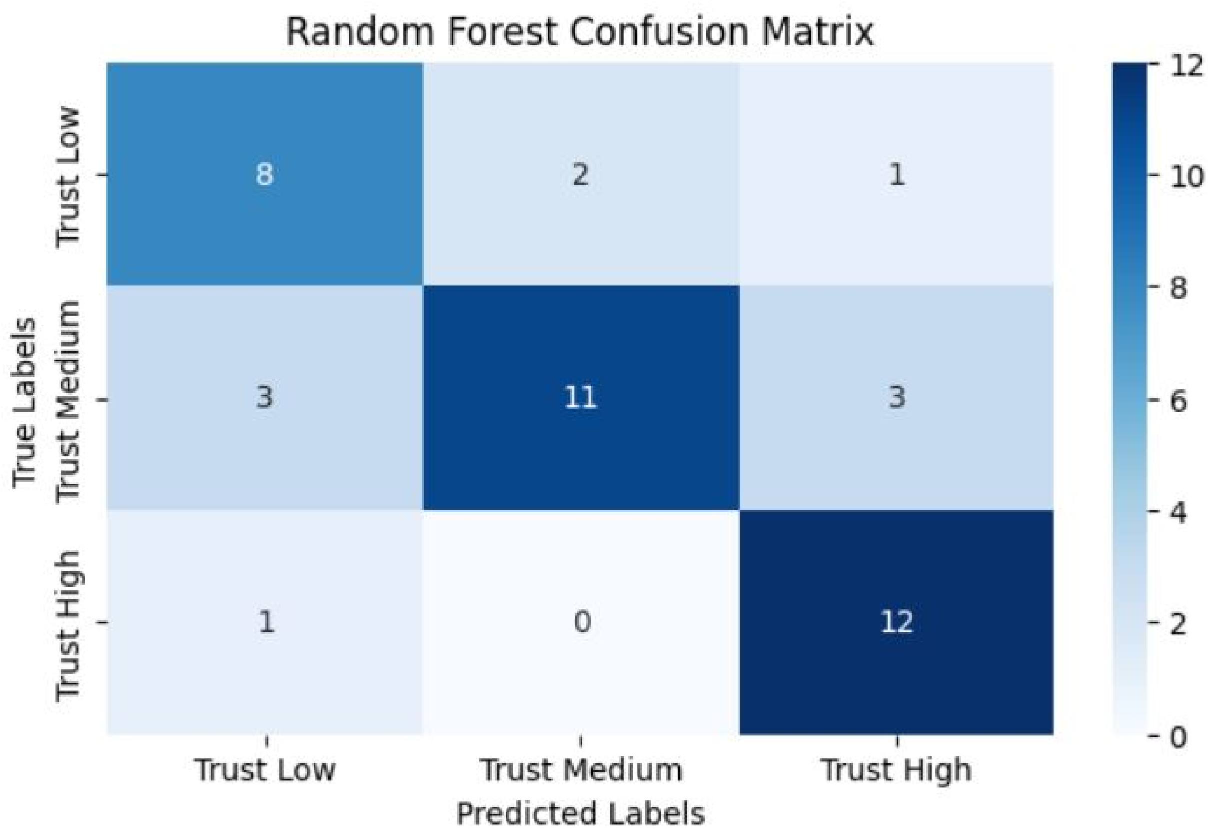

Figure 6.15 Confusion matrix of Random Forest

6.4.2.2.2 The fear of conflict dysfunction

Algorithm	Accuracy	Precision	Recall	F1-score
SVM	0.83	0.90	0.83	0.83
Logistic Regression	0.78	0.86	0.78	0.77
Naïve Bayes	0.66	0.82	0.66	0.604
Random Forest	0.73	0.79	0.73	0.73

Table 6.6 Results for the conflict dysfunction

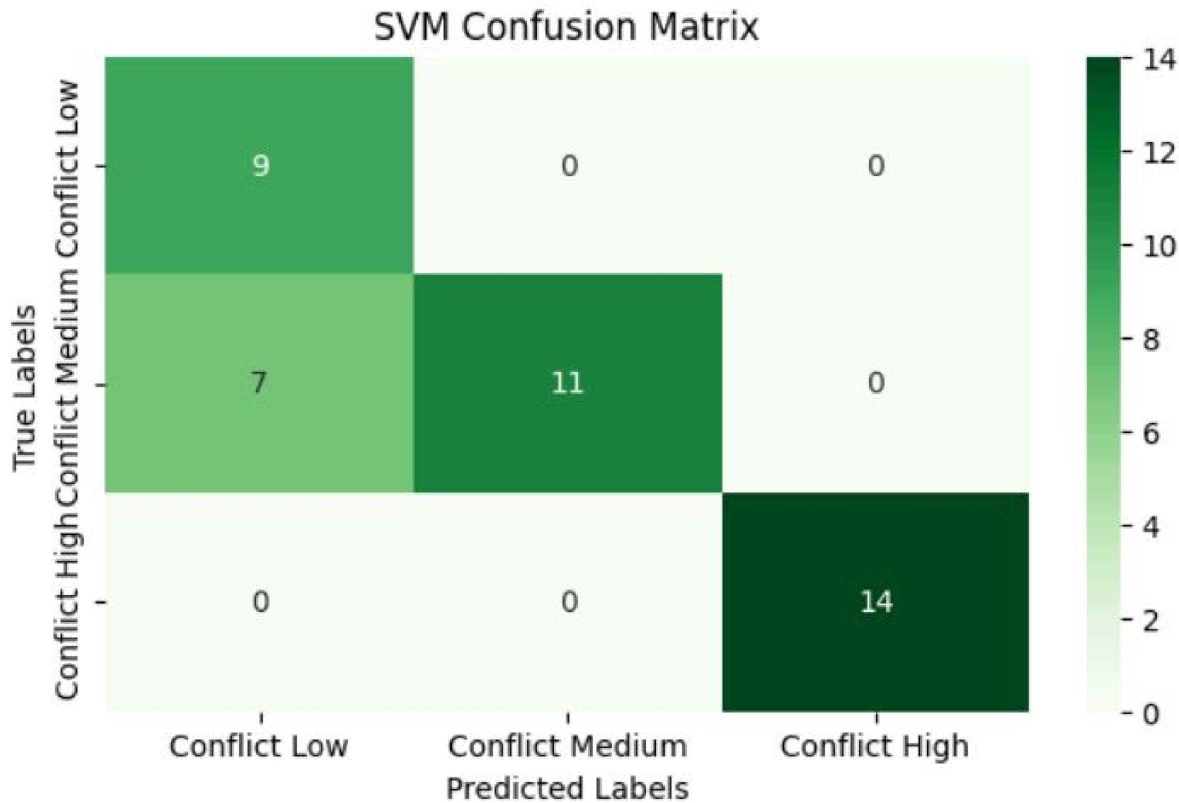

Figure 6.16 Confusion matrix of SVM

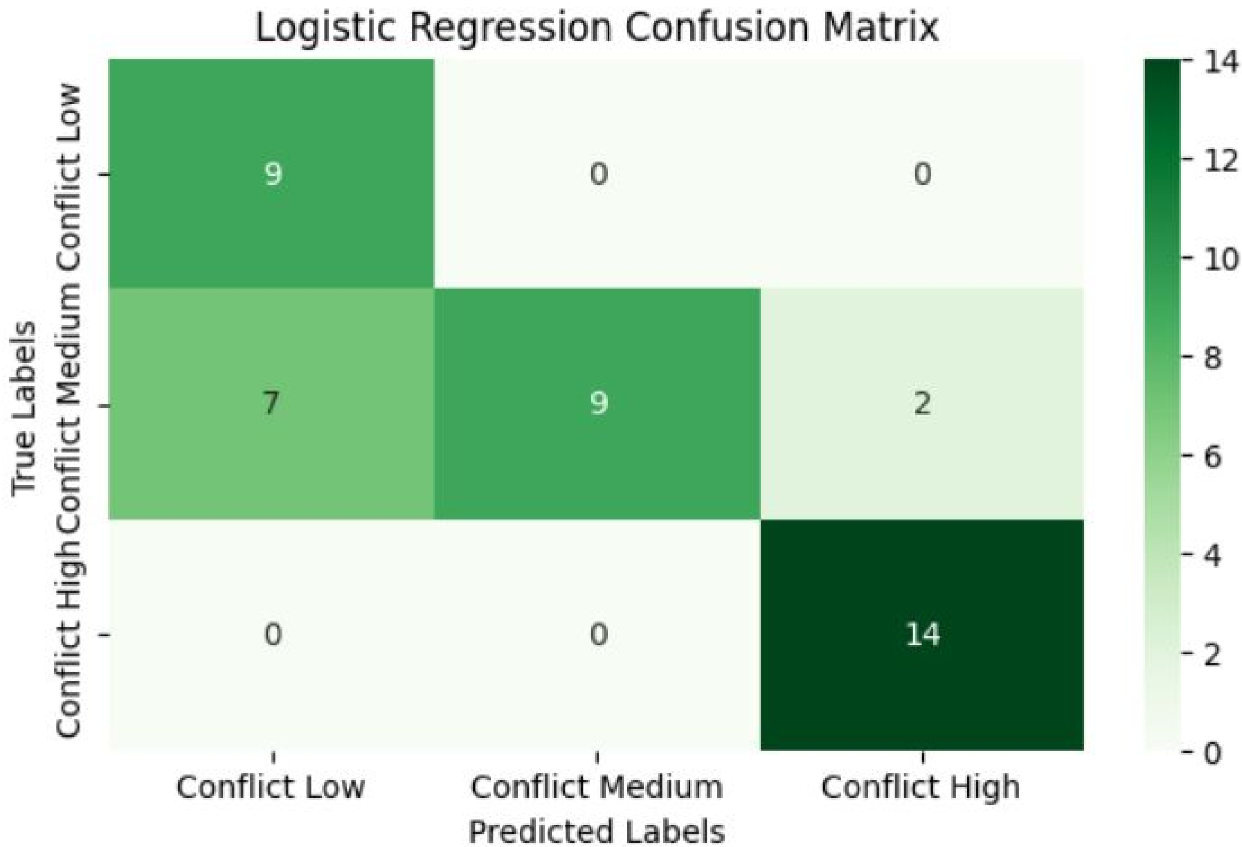

Figure 6.17 Confusion matrix of Logistic Regression

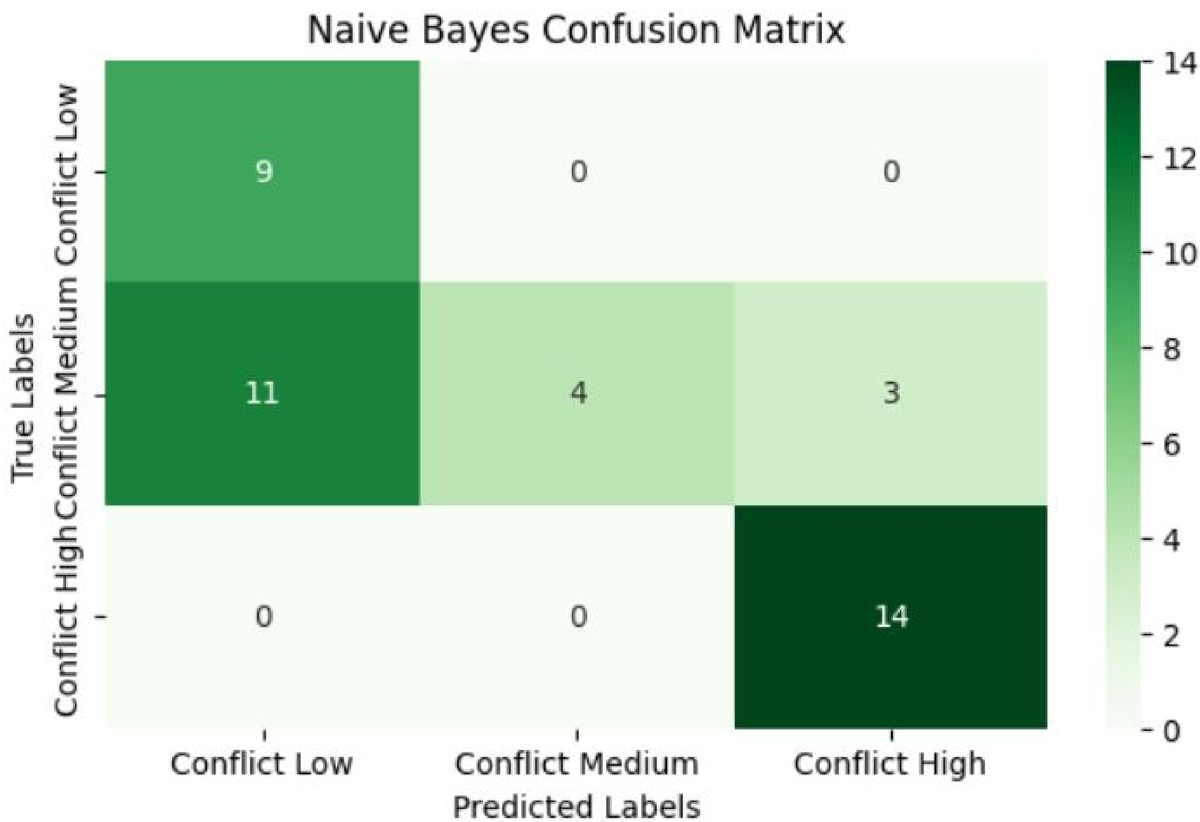

Figure 6.18 Confusion matrix of Naive Bayes

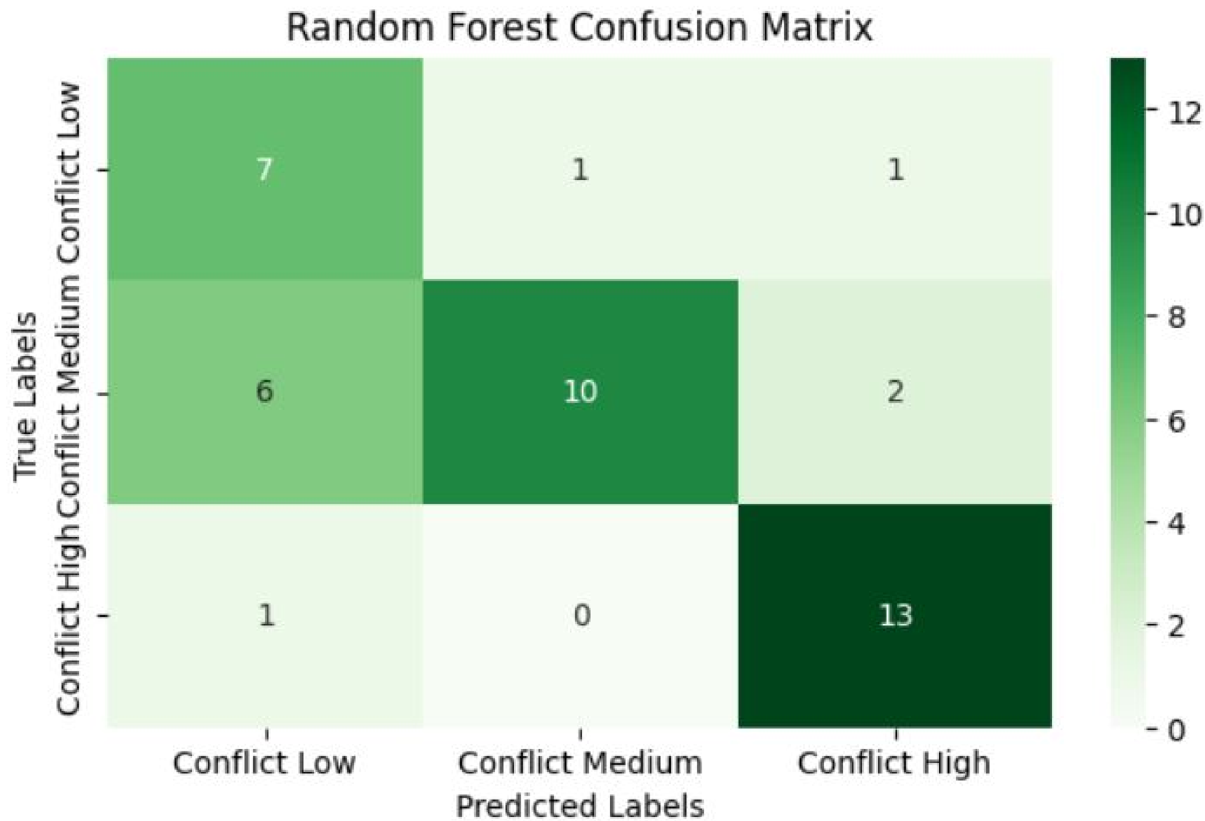

Figure 6.19 Confusion matrix of Random Forest

6.4.2.2.3 The lack of commitment dysfunction

Algorithm	Accuracy	Precision	Recall	F1-score
SVM	0.83	0.86	0.83	0.83
Logistic Regression	0.83	0.85	0.83	0.83
Naïve Bayes	0.78	0.82	0.78	0.78
Random Forest	0.804	0.851	0.804	0.804

Table 6.7 Results for the commitment dysfunction

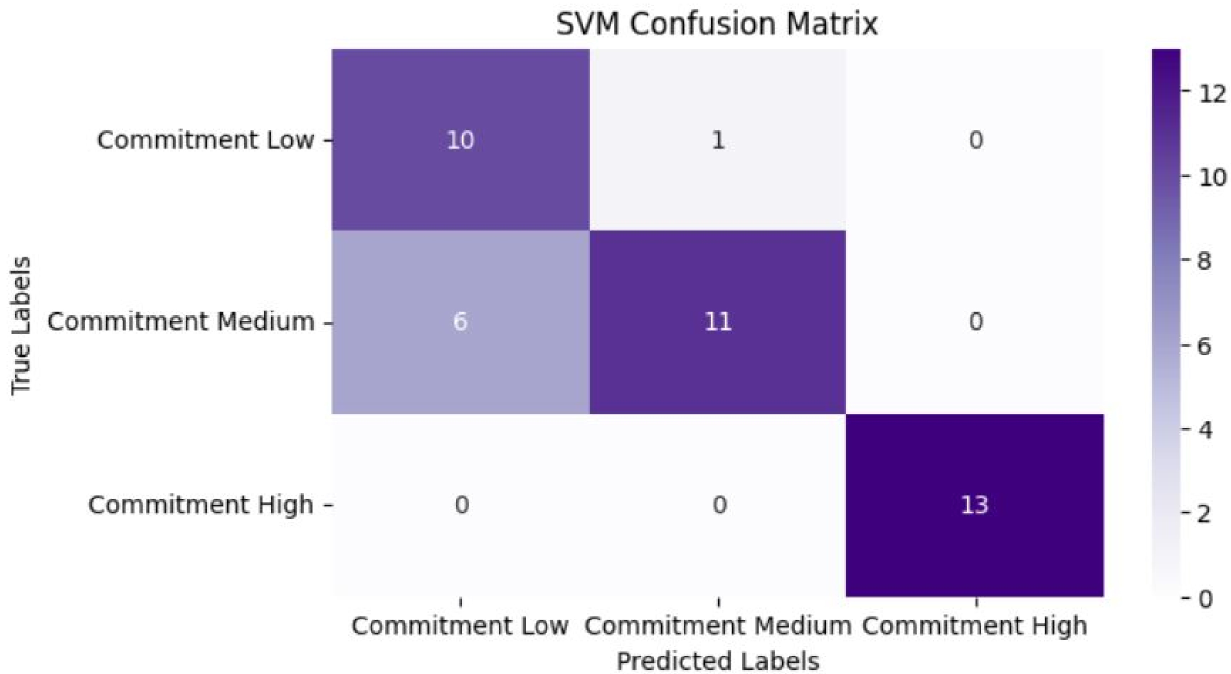

Figure 6.20 Cofusion matrix of SVM

Figure 6.21 Confusion matrix of Logistic Regression

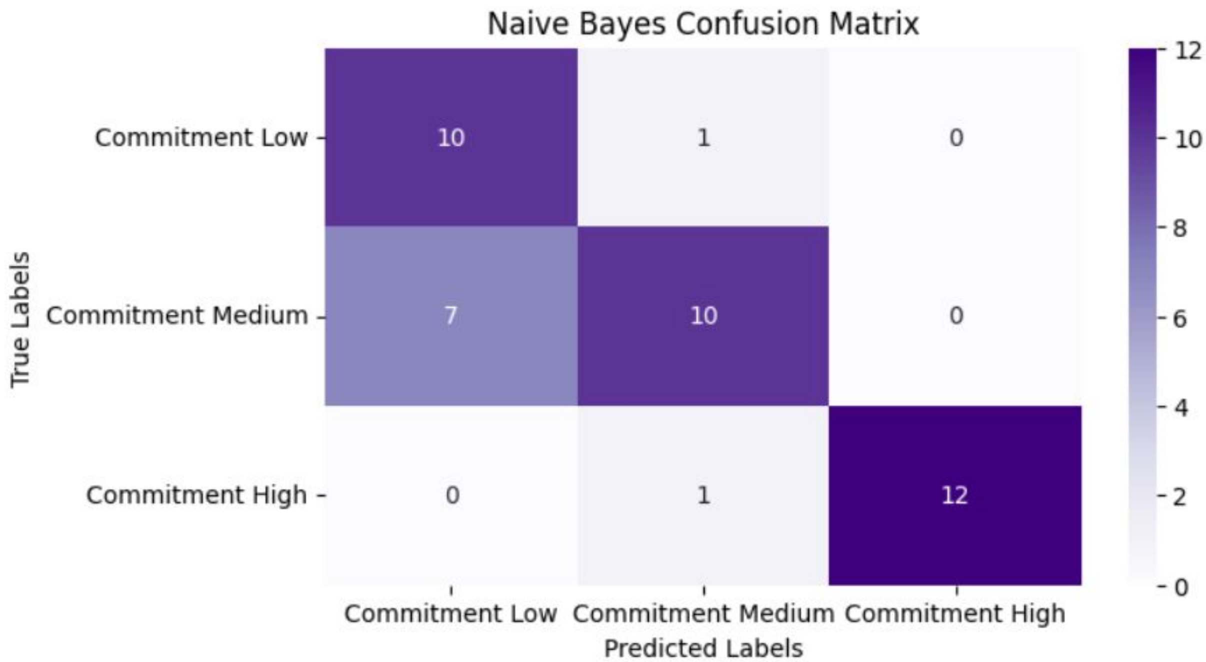

Figure 6.22 Confusion matrix of Naive Bayes

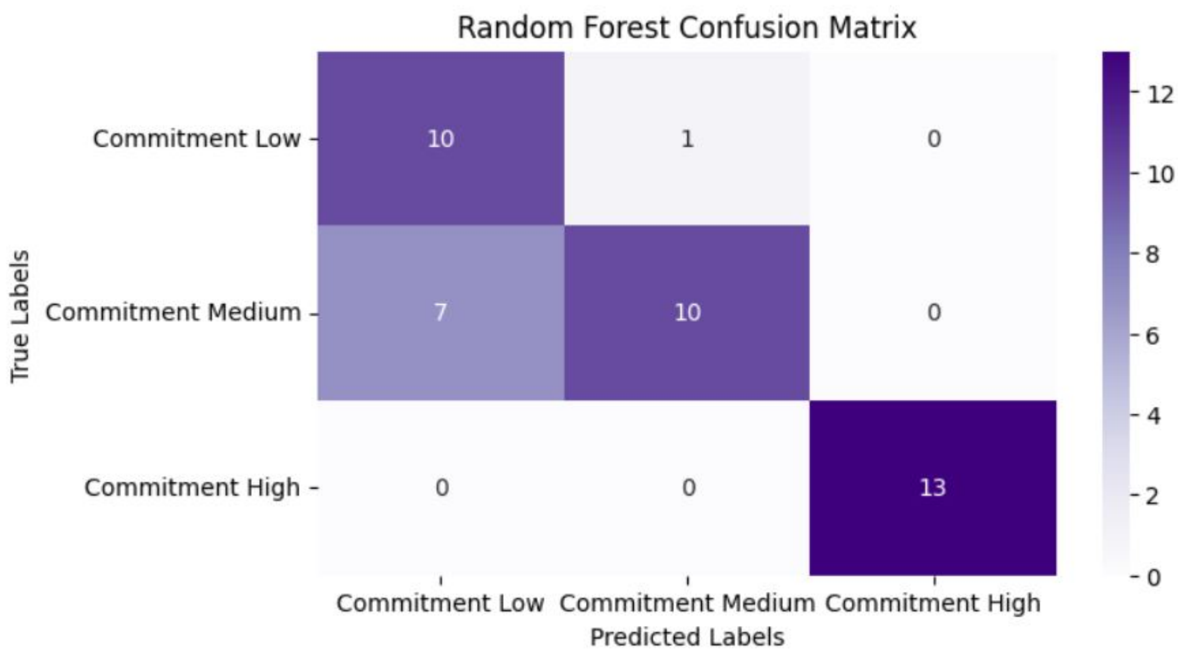

Figure 6.23 Confusion matrix of Random Forest

6.4.2.2.4 The avoidance of accountability dysfunction

Algorithm	Accuracy	Precision	Recall	F1-score
SVM	0.95	0.96	0.95	0.95
Logistic Regression	0.83	0.83	0.83	0.824
Naïve Bayes	0.76	0.77	0.76	0.74
Random Forest	0.78	0.80	0.78	0.77

Table 6.8 Results for the Accountability dysfunction

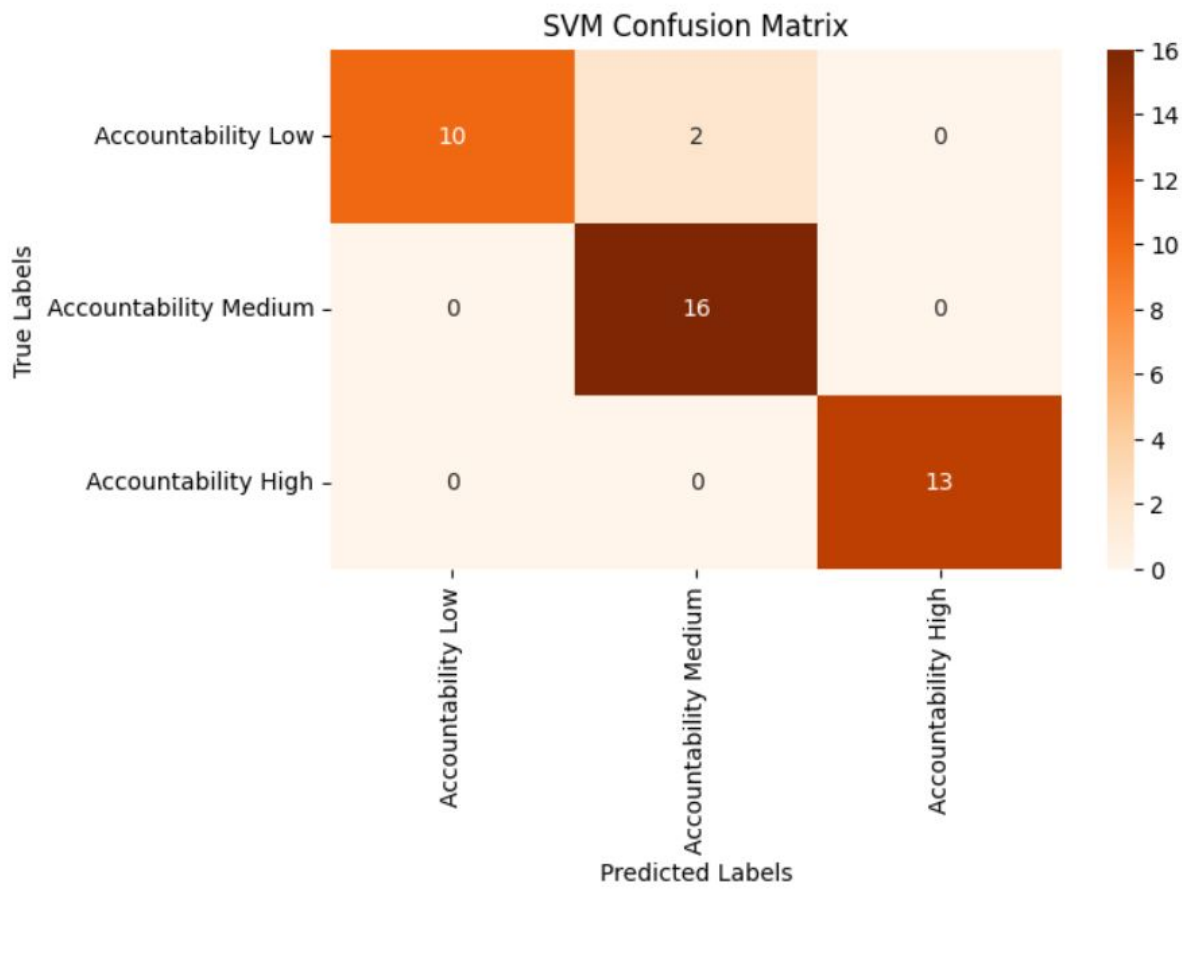

Figure 6.24 Confusion matrix of SVM

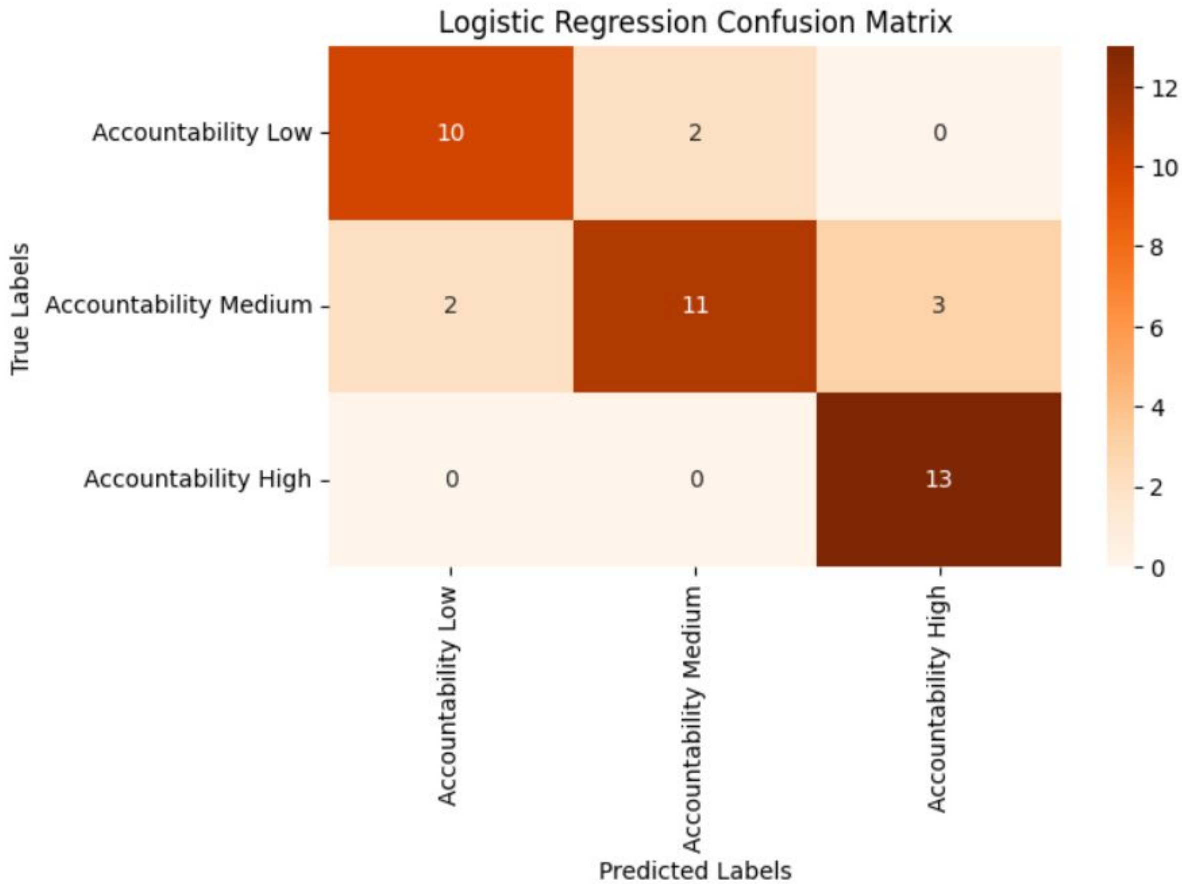

Figure 6.25 Confusion matrix of Logistic Regression

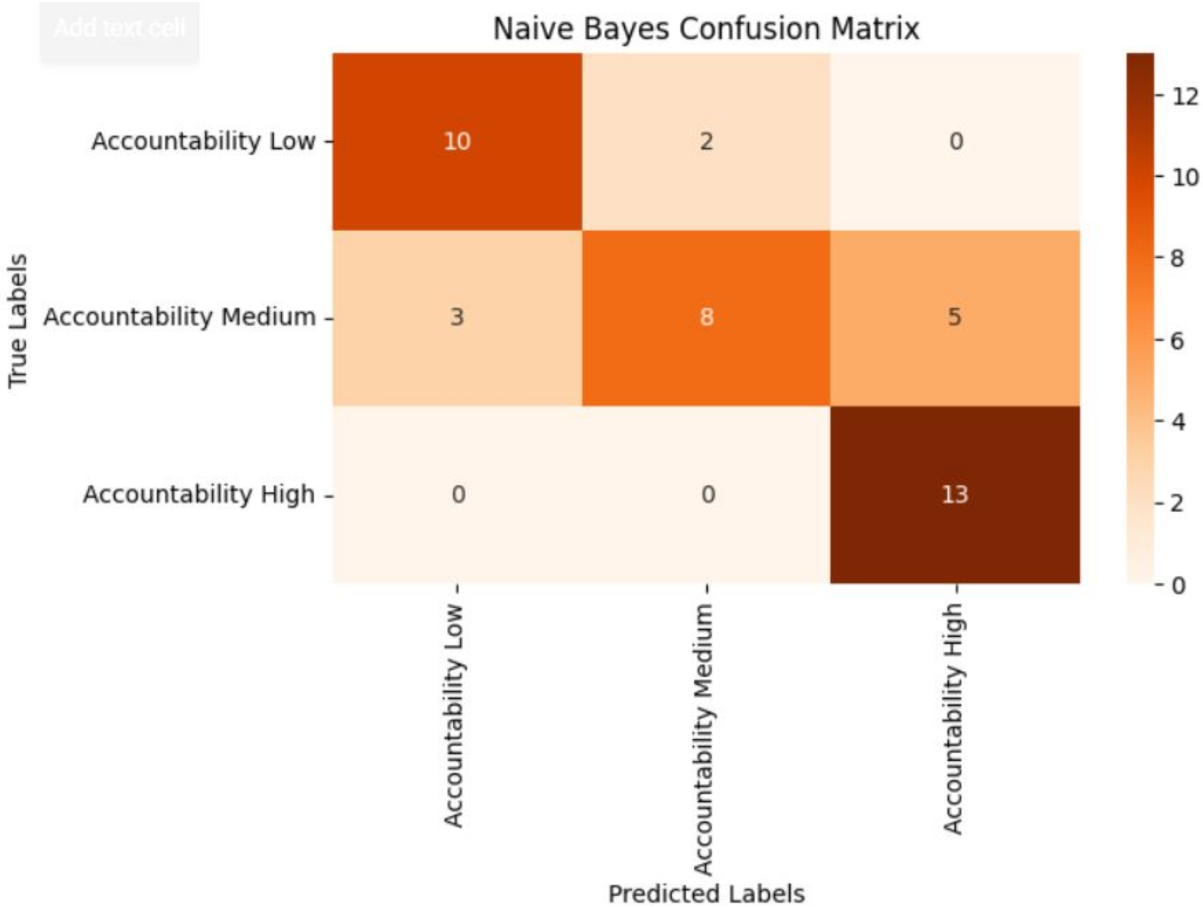

Figure 6.26 Confusion matrix of Naive Bayes

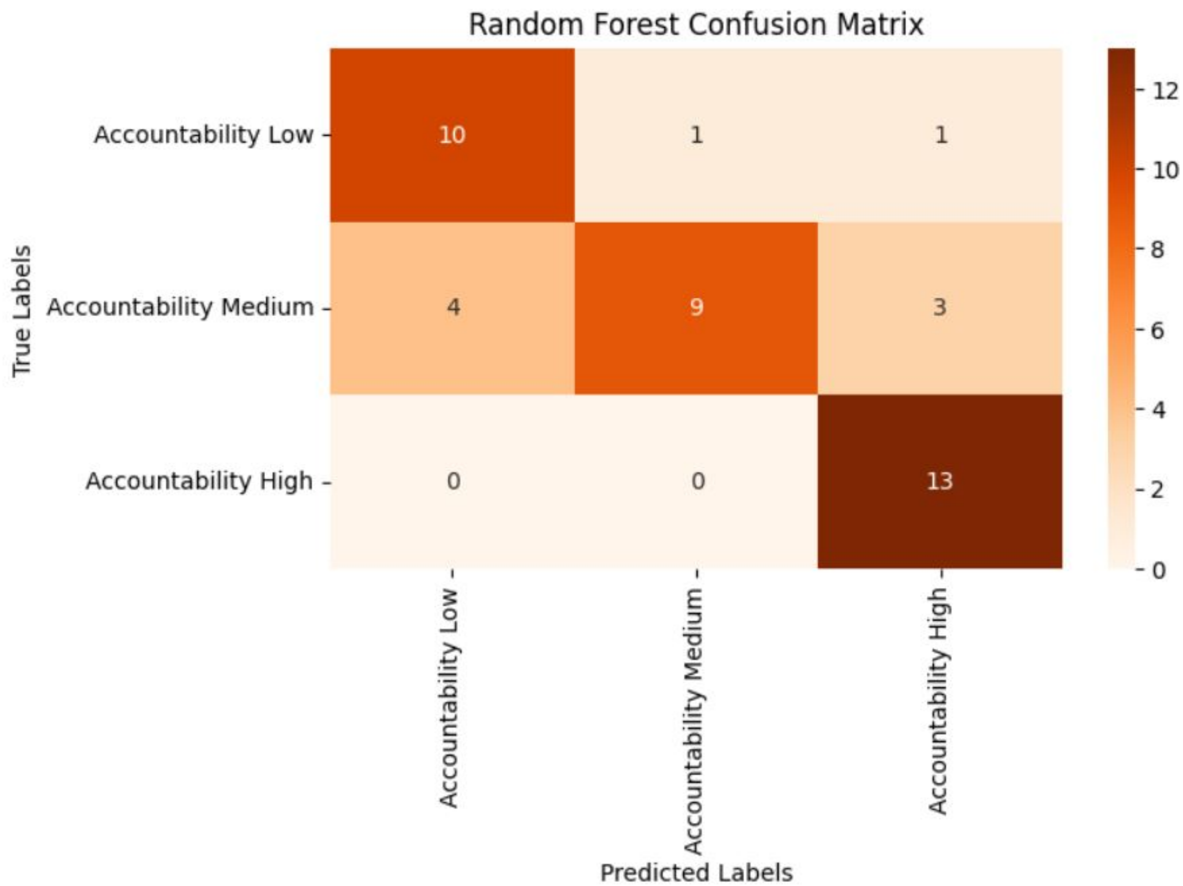

Figure 6.27 Confusion matrix of Random Forest

6.4.2.2.5 The inattention to results dysfunction

Algorithm	Accuracy	Precision	Recall	F1-score
SVM	0.804	0.801	0.804	0.802
Logistic Regression	0.731	0.742	0.731	0.723
Naïve Bayes	0.609	0.634	0.609	0.612
Random Forest	0.707	0.709	0.707	0.700

Table 6.9 Results for the Results dysfunction

Figure 6.28 Confusion matrix of SVM Results

Figure 6.29 Confusion matrix of Logistic Regression Results

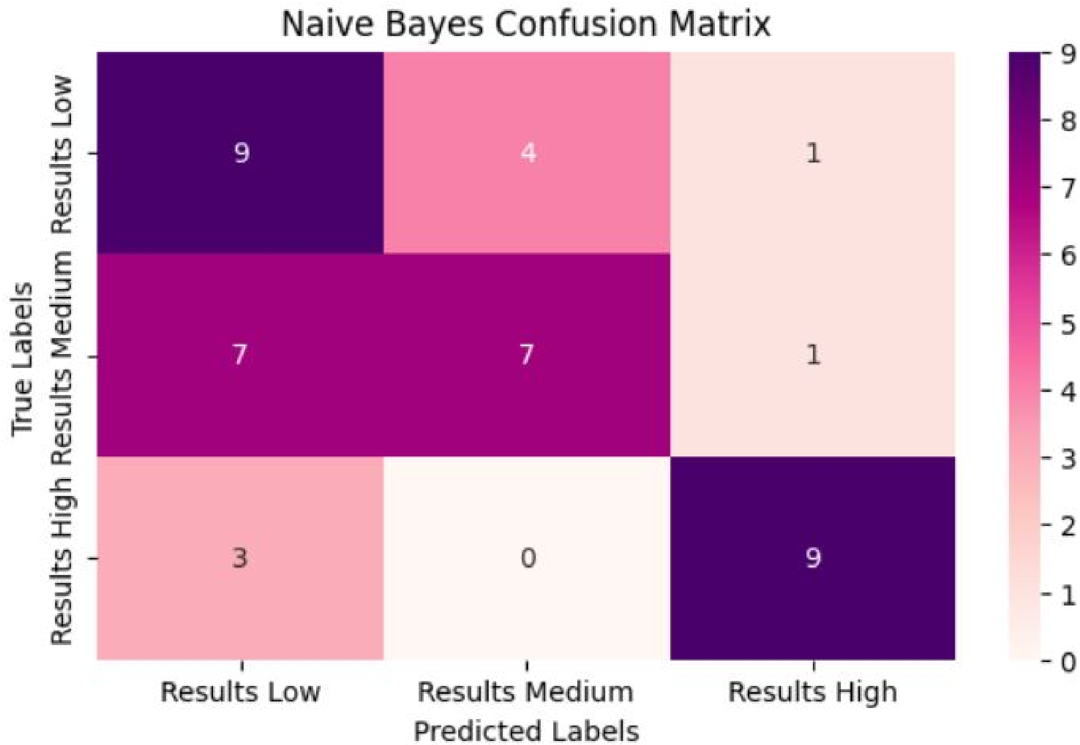

Figure 6.30 Confusion matrix of Naive Bayes Results

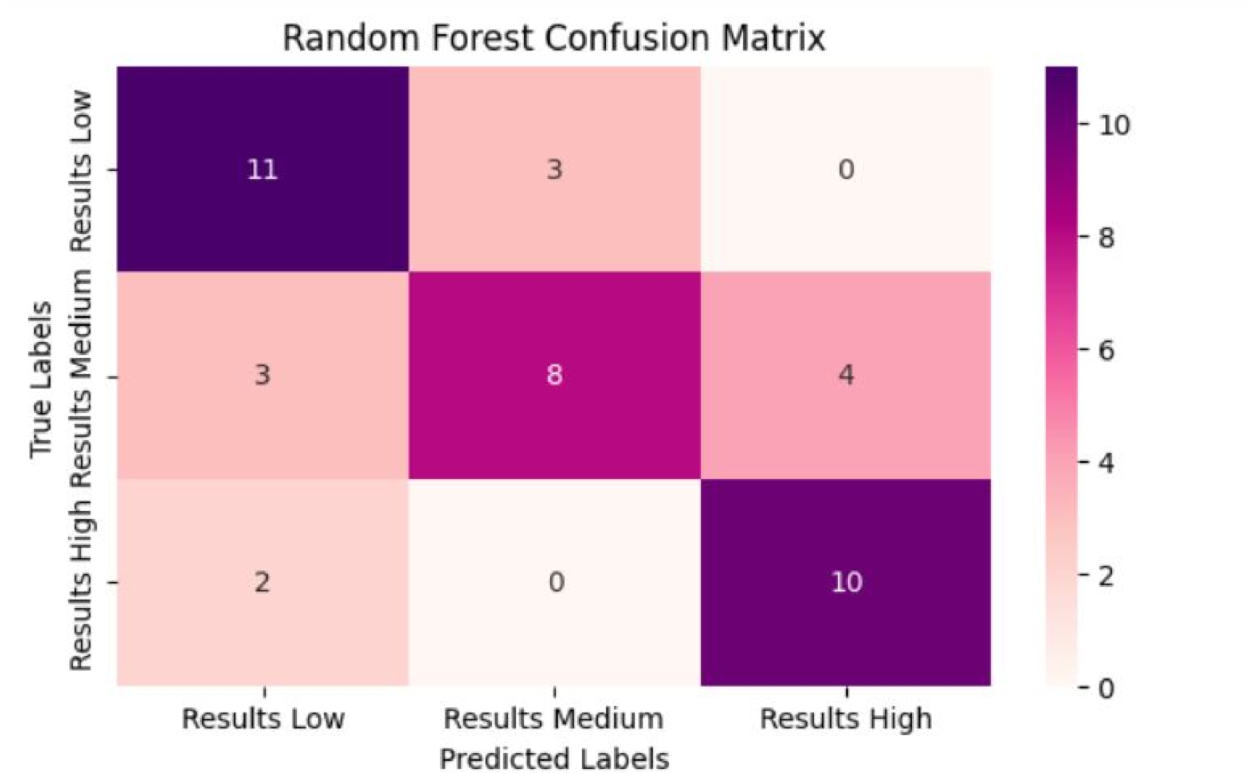

Figure 6.31 Confusion matrix of Random Forest Results

6.4.2.3 Results of the cross-validation

We employed stratified kfold crossvalidation using the sklearn library with ten folds to train and validate the models; further details about stratified k-fold Cross-validation are available at: `https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.StratifiedKFold.html`. The dataset was divided into training and validation sets during each fold, ensuring that each class's proportion was preserved. The models were trained on the training set and evaluated on the validation set, yielding accuracy scores for each fold. Then, we computed the mean accuracy across all folds to evaluate each model's performance on the individual dysfunction dataset.

Table 6.10 shows the mean accuracy of the stratified k-fold cross-validation for the five dysfunctions across the four models.

Dysfunction	Algorithm	Mean Accuracy
Trust	SVM	0.76
	Logistic Regression	0.75
	Naive Bayes	0.72
	Random Forest	0.79
Conflict	SVM	0.79
	Logistic Regression	0.79
	Naive Bayes	0.74
	Random Forest	0.78
Commitment	SVM	0.86
	Logistic Regression	0.83
	Naive Bayes	0.77
	Random Forest	0.84
Accountability	SVM	0.88
	Logistic Regression	0.83
	Naive Bayes	0.77
	Random Forest	0.83
Results	SVM	0.87
	Logistic Regression	0.85
	Naive Bayes	0.79
	Random Forest	0.79

Table 6.10 Mean accuracy of stratified k-fold cross-validation for the five dysfunctions across four models.

We also separately computed the mean accuracy for each level score to evaluate the classifier's effectiveness across different levels because we suspected that medium-level dysfunction would be more difficult to characterize and recognize than Low and High. This comes from well-documented observations in social sciences. Regarding experimental subjects when the answer is unknown, respondents will select 'medium' as a non-committal value to put an answer(Kulas *et al.*, 2008; Kulas et Stachowski, 2009; Baka *et al.*, 2012; Nadler *et al.*, 2015; Chyung *et al.*, 2017; Roberts *et al.*, 2018), as well as some anecdotal evidence from looking at the data ourselves.

Table 6.11 shows the mean accuracy of all level scores for all dysfunctions from each classifier.

Dysfunction Level Score	SVM	Logistic Regression	Naive Bayes	Random Forest
Trust Low	0.81	0.73	0.70	0.82
Trust Medium	0.69	0.67	0.68	0.77
Trust High	0.89	0.80	0.70	0.85
Conflict Low	0.83	0.72	0.68	0.81
Conflict Medium	0.72	0.67	0.67	0.71
Conflict High	0.95	0.80	0.73	0.91
Commitment Low	0.83	0.72	0.67	0.82
Commitment Medium	0.72	0.66	0.66	0.73
Commitment High	0.97	0.81	0.73	0.90
Accountability Low	0.90	0.82	0.75	0.86
Accountability Medium	0.77	0.67	0.67	0.76
Accountability High	0.94	0.91	0.79	0.91
Results Low	0.89	0.73	0.67	0.80
Results Medium	0.78	0.68	0.67	0.75
Results High	0.96	0.75	0.68	0.84

Table 6.11 Mean Accuracy of all level scores for all dysfunctions from each classifier

6.4.3 Analysis of the results

We analyze the results by attempting to answer three questions:

1. Which algorithm performs best/worst (Section 6.4.3.1)?

2. Which dysfunction was predicted best/worst (Section 6.4.3.2)?

3. Which performance level (low, medium, high) was predicted best/worst (Section 6.4.3.3)?

6.4.3.1 Which algorithm performs best/worst

Both the train-test-split technique and the stratified K-fold cross validation showed that SVM performs best, globally, with random forest coming in second, with naive Bayes performing worst.

There were a couple of minor differences between the results obtained with train-test-split, versus stratified K-fold cross-validation:

6.4.3.2 Which dysfunction was predicted best/worst

With train-test-split, avoidance of accountability was predicted best, and the absence of trust was worst, with inattention to results close behind.

6.4.3.3 Which level (High, Medium, Low) was predicted best/worst

- Based on the confusion matrices shown in the previous section, we get the impression that the 'Medium' level performed worst. This is confirmed by a more detailed analysis, as shown in Table 6.12, which focuses on precision, recall, and f1-score results of the medium-level score only for all dysfunctions.

Dysfunction	Model	Precision	Recall	F1-Score
Medium Trust	SVM	0.65	0.65	0.65
Medium Trust	Logistic regression	0.62	0.59	0.61
Medium Trust	Naive Bayes	0.50	0.18	0.26
Medium Trust	Random Forest	0.85	0.65	0.73
Medium Conflict	SVM	1.00	0.61	0.76
Medium Conflict	Logistic regression	1.00	0.50	0.67
Medium Conflict	Naive Bayes	1.00	0.22	0.36
Medium Conflict	Random Forest	0.91	0.56	0.69
Medium Commitment	SVM	0.92	0.65	0.76
Medium Commitment	Logistic regression	0.92	0.65	0.76
Medium Commitment	Naive Bayes	0.83	0.59	0.69
Medium Commitment	Random Forest	0.91	0.59	0.71
Medium Accountability	SVM	0.89	1.00	0.94
Medium Accountability	Logistic regression	0.85	0.69	0.76
Medium Accountability	Naive Bayes	0.80	0.50	0.62
Medium Accountability	Random Forest	0.90	0.56	0.69
Medium Results	SVM	0.73	0.73	0.73
Medium Results	Logistic regression	0.80	0.53	0.64
Medium Results	Naive Bayes	0.64	0.47	0.54
Medium Results	Random Forest	0.73	0.53	0.62

Table 6.12 Models Performance for the Medium level score

- The absence of trust was worst, with inattention to results close behind

6.4.3.4 Analysis of the Cross-validation Results

Based on the acquired accuracy results as shown in table 6.10 and table 6.11 using cross-validation, the following results were discovered:

1. Which algorithm performed best:

    - SVM and Random Forest achieved the best performance across most dysfunctions.
    - Logistic regression emerges as a competitor and performs better than Random forest with conflict and results dysfunctions.

2. Which algorithm performed poorly:

    Naive Bayes had lower accuracy when compared with the other algorithms.

3. Which dysfunction predicted the best:

    Accountability dysfunction was predicted the best among the five dysfunctions analyzed, with the highest mean accuracy of 0.88 with the SVM algorithm.

4. Which label level (High, Medium, Low) performed best/worst:

    We noticed from the mean accuracy table 6.11 that the medium scores have lower accuracy values when compared to the low and high-level scores across all dysfunctions and classifiers. This lower accuracy indicates a problem in identifying medium-level, which might be due to the following:

    - The challenge in accurately recognizing and distinguishing moderate dysfunctions arises from the inherent ambiguity in the dialogues generated by ChatGPT.
    - All the models (classifiers) have shown low accuracy with medium scores, indicating that the problem is not with the classifier but with the medium-level dialogues.

6.5 Conclusion

The analysis shows how machine learning models can identify and categorise teamwork dysfunctions based on Lencioni's model(Lencioni, 2012). For each of the five dysfunctions, average accuracy scores were calculated for low, medium, and high levels. However, there were difficulties in classifying moderate cases, which often had lower accuracy than low and high levels for all dysfunctions.

The results highlight that recognising medium-level scores is challenging. This may be due to ChatGPT's limitations in accurately representing slight differences in dialogues. Lencioni's model also focused on identifying only high and low-performance levels through specific statements, leaving the moderate levels less defined. However, we designed contradiction prompts with medium-level scores to distinguish the low and high scores for the medium level. As a result, low performance in this category was observed due to troubles that arose when classifying cases with moderate levels of dysfunction.

Therefore, an alternative strategic approach to address this would be to retrain the models only on low and high levels of dysfunction to increase their reliability in the classification process. Thus, this will enable faster identification of team members who can be classified at the extreme ends of severity while dealing with less ambiguity. In this case, the main idea is that a machine learning model can misclassify a moderate-level dysfunction as either low or high because such classifications are typically ambiguous.

In conclusion, although these machine learning approaches demonstrated promising results in classifying low and high levels of dysfunction in teams, it is evident that there were still challenges in accurately identifying cases with moderate but dysfunctional behaviour. Consequently, by focusing on ambiguities and difficulties that come with such data sources, future upgrade iterations should increase the accuracy of models, hence being able to detect team dysfunctions more effectively, thus supporting the improvement of team performance in real-life situations.

CHAPTER 7
CONCLUSION

In this conclusion chapter, We first summarize the work (Section 7.1). Next, we outline the major contributions of the work (Section 7.2). We conclude the chapter by highlighting areas for future research (section 7.3).

7.1 Summary of the work

7.1.1 Research question

As the manager of the e-learning department at my university, I have long been interested in the impact of social media applications on student engagement and performance. There is conflicting literature on the topic. Some studies have shown a negative impact on student engagement and performance, because of the distractions and the addictive nature of many such applications (see e.g. (Gok, 2016)). Others showed a positive impact due to increased communication between teachers and learners, but also between learners, sharing information and problem-solving skills (Legaree, 2015).

With the onset of the COVID pandemic, all learning and communication shifted online. There is anecdotal evidence to suggest an increase in team dysfunctions within student team projects. This could well be due to the degradation in students' mental well-being, due to the social isolation that accompanied the early stages of the pandemic. However, a similar phenomenon was observed well before the pandemic. Indeed, an informal survey of academics found that they anecdotally observe dysfunctions to be amplified when students start working together online (Lam *et al.*, 2005). At the same time, online communication tools are used daily, and successfully, by international decentralized teams to conduct mission critical projects.

This led to the more interesting research question:

Does the increase in team dysfunctions, in the context of student team projects, come from the inadequacy of social media app communications functionalities to the kinds of teamwork modalities required by academic team projects?

This raises the question: what is special about academic team work.

Our research has focused on identifying which groups have more ability to perform fruitful discussions vs which ones have poor performance in their group chats. To do so, we searched for dialogue datasets on the web, and after a deep search, we did not find data labelled with team dysfunctions. This leads us to think of labelling our data manually, which is time-consuming and resource-intensive. Then, we experimented with the Enron dataset to start identifying teamwork dysfunctions, and we used zero-shot classification to label Enron data with the five team dysfunctions. However, it failed to learn each dysfunction, so we transitioned to utilising the chatGPT API as a foundation for constructing our dataset. We used four distinct machine-learning algorithms to train the generated datasets. Support Vector Machine (SVM), Logistic Regression, Naïve Bayes, and Random Forest. These algorithms learn from our labelled data to recognise patterns and identify team dysfunction on new, unseen data.

7.1.2 Methodology

To test our hypothesis mentioned above, which is the noticeable increase in team dysfunctions among students due to the inadequacy of social media applications' communication functionalities for teamwork, we presented the teamwork styles based on the literature in organizational theory to propose a classification of group work styles along the cooperation versus collaboration spectrum. We identified the types of projects that require these different group work styles, which is explained in detail in the chapter (3).

Observing that certain project types possess unique communication requirements unfulfilled by existing tools does not inherently suggest dysfunctional team dynamics. Recognizing that the inadequacy of communication tools typically does not culminate in dysfunctional teams outright; instead, it may result in slower progress or frustrated team members. It is common across various fields, including Information Technology (IT), for teams to encounter shortcomings in tools, frameworks, or languages, which may elicit grievances. Hence, we needed to demonstrate what teamwork dysfunctions mean, as presented in detail in the chapter (5.2). Then, we identified them using natural language processing (NLP) and the development of a sentiment analysis model based on multiple machine learning classifiers to diagnose these dysfunctions within team communication.

The identification of team dysfunctions is considered a supervised classification, which requires performing the following steps:

1. Identify the features of team communications traces that indicate the various dysfunctions.
2. Acquire or develop a labelled dataset of team communication traces with correctly identified team dysfunctions.
3. Use the labelled dataset to train a machine learning model to recognize those features in team communication traces.
4. Use the trained model to detect these dysfunctions in team communication traces.
5. Evaluate the performance of the used models to measure their accuracy.

Building a trained model for sentiment analysis requires a good-quality training dataset. Data collection is an essential aspect of building a trained machine-learning model. Many data resources exist, such as social media platforms, customer web reviews, and data repositories like Kaggle, GitHub, and the UCI Machine Learning repository.

Finding suitable datasets that exhibit teamwork dysfunctions was a challenge. Initially, we experimented with the Enron dataset, comprised of email exchanges preceding the company's infamous accounting scandal and subsequent bankruptcy (Cohen, 2023), which were believed to reflect a dysfunctional organizational culture. However, the Enron dataset posed two significant obstacles. Firstly, it lacked labels associating email exchanges with specific team dysfunctions. We considered using it with zero-shot learning, an approach wherein we train models without using any labelled examples. When we tried to validate manually the labels assigned by the model using zero-shot learning, we realized that the human subjects who did the validation did not agree on the labels. Secondly, the dataset primarily consisted of one-way communications, making it challenging to identify genuine exchanges and further complicating labelling efforts. the detailed experiment with the Enron dataset is presented in chapter (4).

Thus, we explored an alternative technique involving ChatGPT to generate dialogues that exhibit teamwork dysfunctions based on precise characterizations as identified by the Lencioni model (Lencioni, 2012), which links each dysfunction to observable behaviours in team member communications. We designed prompts based on Lencioni's statements to generate dialogues reflecting these manifestations. This method enabled us to have approximately 200 dialogues for each of the five dysfunctions across three levels of scores(Low, medium, high), totalling 1000 dialogues. The detailed approach for using chatGPT to generate dialogues is presented in the chapter (5).

After creating our datasets, we performed model training using supervised machine learning. Four distinct machine-learning algorithms were used to train the model with the generated datasets. Support Vector Machine (SVM), Logistic Regression, Naïve Bayes, and Random Forest. These algorithms learn from our labelled datasets to recognize patterns and make predictions on new, unseen data. Our training was done in five different models per dysfunction to detect its presence and severity (low, medium, high). Doing so makes it possible to accurately classify each dysfunction in the conversation or dialogue. Training the models one dysfunction at a time lets them learn the unique patterns and feature space for each teamwork dysfunction. It results in highly accurate identification and understanding of the underlying issues.

Then, we employed measurements to assess the model's performance and capabilities in accurately identifying teamwork dysfunctions. We used multiple metrics: accuracy, precision, recall, and F1-score. We also employed stratified k-fold to get more reliable results, using (K) different breakdowns of the dataset between training and test data and averaging the results. When dealing with a multi-class classification problem, the *stratified* K-fold cross-validation ensures that each one of the K subsets is representative of the distribution of the classes in the full dataset. Our obtained results are shown in the subsequent section 7.1.3

7.1.3 Results

We presented our findings in three different ways:

1. We compared how each of the four algorithms performed against the five dysfunctions using train_test_split to handle the testing. Comparing the performance of the four algorithms for each provided an alternative presentation of results aimed at identifying different trends in algorithm performance, noting when one algorithm outperformed the others.
2. We ordered our results by dysfunction as another view of the data, processing all four algorithms one after the other for each dysfunction.
3. We presented our last set of results using stratified K-fold cross-validation to better identify robust performance trends across different folds and data subsets in assessing algorithm performance.

We analyzed the results by attempting to answer three questions:

1. Which algorithm performs best/worst?
2. Which dysfunction was predicted best/worst
3. Which performance level (low, medium, high) was predicted best/worst

The train-test-split technique and the stratified K-fold cross-validation showed that SVM performs best globally, with random forest coming in second and naive Bayes performing worst. There were minor differences between the results obtained with train-test-split, versus stratified K-fold cross-validation.

With train-test-split, avoidance of accountability was predicted best, and the absence of trust was worst, with inattention to results close behind. Meanwhile, with stratified k-fold cross-validation, avoidance of accountability dysfunction was predicted to be the best among the five dysfunctions analyzed, with the highest mean accuracy of 0.88 with the SVM algorithm.

We get the impression from confusion matrices and the mean accuracy that the 'Medium' level performed worst. This lower accuracy indicates a problem in identifying medium-level, which might be due to the challenge in accurately recognizing and distinguishing moderate dysfunctions arising from the inherent ambiguity in the dialogues generated by ChatGPT. All the models (classifiers) have shown low accuracy with medium scores, indicating that the problem is not with the classifier but the medium-level dialogues.

7.2 The main contributions of the thesis

This study addresses the challenging problem of finding ways to understand and manage group dynamics in real-time situations, explicitly focusing on detecting and characterising dysfunctions in how professionals work together. We propose a first computational approach, which applies machine learning techniques from computational linguistics and insights from organisational psychology, to develop a classification model of team dysfunctions that can detect them in dialogue data. Our proposal paves the way both to improving the theoretical understanding of ways in which teams can go awry within a field that is still new and extant and to providing valuable tools for organisations that want to tune the way their teams work to support the work of their members best and increase their performance. The following contributions in group dynamics and computational linguistics are listed below.

7.2.1 Mapping work styles to communication needs

Previous literature has mentioned two group work styles, cooperation and collaboration. *Cooperation* focuses on an effective *division of labor* between the team members, where project deliverables are broken down into fairly independent tasks that can be undertaken by individual team members working separately. By contrast, *collaboration* requires individuals to work *together* on the same deliverables. It involves knowledge sharing and constant communication.

As part of my work, I attempted to map work styles to communications needs (see Sections 2.3 and 3.5), in general, and within a learning context. We also recognized that the same group project may require different work styles–and thus have different communication needs–at different phases of the project. This work, while preliminary, is central to our research hypothesis about the causes of increase in dysfunctions in student team projects during the pandemic.

7.2.2 Identifying team dysfunctions using sentiment analysis techniques

Diagnosing the work dynamics within a team is challenging, particularly in real-time (Lencioni, 2012). Current methods rely almost exclusively on subjective assessments by the team leader or post-hoc analyses, both of which are time-consuming and naturally biased. There is a pressing need for a model that can provide an objective, scalable, efficient approach to classifying and dealing with these dysfunctions as they occur within interpersonal dialogues in real-time (Martínez-Moreno *et al.*, 2009).

Sentiment analysis techniques have been used extensively in the recent past to analyse customer reviews of various products and services, to assess the polarity of these reviews, as a whole, or about specific aspects of those products and services.

We proposed to use sentiment analysis techniques to diagnose team dysfunctions by analyzing team communication. However, it is not all that obvious:

1. Whether those dysfunctions will manifest themselves in team conversation, especially within the context of–typically–sanitized professional conversations.
2. If they do manifest themselves, how, and
3. Whether the cue are salient enough to be recognizable by a machine learning model.

Luckily, Lencioni helped answer the first question, by associating, with each dysfunction, half a dozen team member behavioral patterns, some of which have communication "footprints" (Lencioni, 2012). However, things like *fear* of conflict are difficult to asses, because they may be indistinguishable from *lack* of conflict, i.e. genuine agreement!

Notwithstanding the partial human validation (Section 6.4), the fact that we were able to get good results with cross-validation shows that our hypothesis was plausible: there exist salient traits in team conversations that are indicative of team dysfunctions, and that are recognizable by machine learning algorithms.

7.2.3 An exploration of the Enron Dataset and zero-shot learning

While the Enron dataset proved inappropriate for our needs (Section 4.4), working with the data set was interesting in its own right, because of the company's history. The Enron dataset was supposed to reflect a corrupt company business culture, and that is somewhat evident in some of the emails that we looked at. However, conspiring to commit unethical or illegal acts does not necessarily mean team dysfunction.

Because the Enron dataset was not labeled, I had to explore different automated labeling techniques, and by extension, transfer learning and zero-shot learning. The experiment was inconclusive (Section 4.3.2), because of the nature of the data (Section 4.4), but it gave me the opportunity to learn about, and use BERT.

7.2.4 Using ChatGPT to generate a labelled dataset

The decision to use chatGPT to generate dialogues exhibiting teamwork dysfunctions was sort of a last resort solution, after failing to find a labeled dataset, or to label the Enron dataset.

At first glance, and with hindsight, this seemed as the natural thing to do. At a very basic level, ChatGPT–and LLMs in general–are good at generating text that is the most likely "reply" to the provided prompt, based on the statistical patterns emerging from billions of utterances ingested by the various ML models. This simple metaphor, exploited through complex and careful engineering, has led to many uses of this text generation/association capability. The question then became: if "told" about the various team dysfunctions, and how they manifest themselves in interactions between people, could ChatGPT generate dialogues that exhibit those dysfunctions?

The following elements lead to answer the question with a qualified *yes* (Section 5.5):

1. Manual inspection of a sample of the generated dialogues showed that the dialogues in question did exhibit the targeted dysfunctions, albeit sometimes in a literal/unsubtle way.
2. A preliminary evaluation with human subjects, that used an admittedly perfectible experimental protocol, showed a high enough agreement between human subjects and ChatGPT [1]. Minimally, this warrants further refinements of the dialogue generation, and of the validation protocol.
3. We were able to train a machine learning model to recognize dialogues exhibiting the various dysfunctions. This means that the dialogues exhibit salient enough characteristics that can be recognized (see next Section).

Much remains to be done to refine the dialogue generation methodology, and the validation protocol 7.3.1.

7.2.5 A *verification* methodology for the dialogues generated by ChatGPT

Validating the dataset generated by ChatGPT requires that, for each prompt corresponding to a specific team dysfunction (e.g., the prompt 'team members do not admit weaknesses' for the dysfunction 'lack of trust'), we give the dialogues generated by ChatGPT for that prompt to human subjects, and ask them to assess whether the generated dialogues do exhibit the corresponding dysfunction ('lack of trust'). We did conduct a preliminary *validation* experiment, described in Section 5.5, and the results showed great promise (see Section 5.5.4).

[1] Recall that we asked ChatGPT to generate dialogues exhibiting three different levels of performance, for each of the dimensions. The agreement rate for the low and high performance levels was of 71%, and 86%, respectively. For the "medium" performance level, the agreement between ChatGPT and human subjects was 6%.

By *verification*, we mean assessing an *intrinsic* quality of the dataset: can a machine learning model correctly classify (recognize) the dialogues generated for a particular dysfunction. This is actually far from obvious, for several reasons, some methodological, and some having to with ChatGPT itself. First, for each of the five team performance dimensions, we used half a dozen prompts, corresponding to: 1) the different levels of performance, for that dimension, and 2) the different manifestations of the corresponding dysfunction, as identified by Lucioni (Lencioni, 2012). It is far from obvious that a *single* model could properly classify the dialogues generated by different prompts, and for three different performance levels. This confirms that, there are indeed, salient features that are common to the dialogues that exhibit a given level of performance for a given performance dimension, from high performance to outright dysfunction. Second, ChatGPT remains a blackbox, despite what we know about LLMs in general, and ChatGPT's own documentation, and what come to be known as *prompt engineering*: poorly designed 'prompting' strategy, or poorly crafted prompts could very well result into dialogues bearing no relation to the team performance dimension, nor its level (high, medium, dysfunctional).

In our case, the accuracy metrics reached 90%, for some combinations of (learning algorithm, dysfunction) (Section 6.4.2). This means that the methodology is sound.

7.3 Directions for future research

7.3.1 Validating the dialogues generated by ChatGPT with human subjects

To generate dialogues exhibiting the various team work dysfunctions, we followed the protocol explained in ChatGPT's documentation (see Section 5.3), including: 1) priming ChatGPT with a definition of the various dysfunctions, and 2) trying out different prompts, fine-tuning some of the words in the prompts to elicit the proper responses. Like we mentioned in Section 5.5, a preliminary inspection of the generated dialogues, while we were refining the prompts and ChatGPT's parameters, revealed that the dialogues did exhibit the targeted dysfunctions. We proposed in Section 5.5 a more systematic validation. We planned a two-phase validation protocol, with: a) a preliminary validation to get an idea about the results, and help design a more detailed protocol (Section 5.5.3), followed by b) a more precise and detailed protocol, using the lessons learned from the first phase (Section 5.5.2).

We did conduct the first phase, described in Section 5.5.4, in less than ideal circumstances: the experimental subjects were Master's level students, for whom English–the language of the dialogues–is often the third language, at 9:30 pm, after the end of a mid-term exam. Further, the data randomization and distribution that we planned could not followed.

However, despite its shortcomings, the experiment did achieve the desired outcomes:

1. It showed a high enough agreement between ChatGPT and human subjects–over 80% for some prompts–to warrant a more thorough validation;
2. It did confirm the intuition we had about the problematic nature of the "medium" performance level;
3. It identified a number of TODOs and NOT-TODOs for the second phase of the validation.

Thus, we need to conduct a more thorough validation through human subjects by:

1. Integrating the lessons learned from the preliminary validation described in Section 5.5.4.
2. Increasing the sample size (dialogues) and the number of participants.
3. Validating all the five dysfunctions, not only the first dysfunction (Trust).
4. Validating dialogues from each prompt, which will tell us which prompt is better than others for generating more accurate and related dialogues about that dysfunction.

In particular, we would like to make a final determination about what to do about medium performance levels for the various dysfunctions.

7.3.2 Enhance the dialogue generation

We used different prompts, based on the different cues identified by Lencioni to recognize and diagnose team dysfunctions (Lencioni, 2012). However, both the dysfunctions, and the prompts for a given dysfunction, have different salience. For example, lack of trust may be easier to diagnose than fear of conflict, which can be confused with 'agreement'. Similarly, for a given dysfunction, any cue based on the *occurrence* of some behavior is stronger and easier to detect than a cue about the *absence* of some behavior.

In our experiment, we limited our manipulation of the prompts to make sure that the generation methodology is reproducible (Section 5.3). We could improve the generated dialogues by explicitly recognizing the importance of including human-in-the-loop (HITL) in the crafting of the prompts, by revising Lencioni's cues, or developing new ones based on the since published literature on team dysfunctions. HITL uses supervised machine learning and active learning involving humans in model development and testing. This involvement of humans enables the machine to learn better and achieve more reliable and accurate results (Wu *et al.*, 2022).

7.3.3 Answering the original research question

Recall that the original motivation of our research was to identify the reasons for which student team work dysfunctions *increased* during the pandemic when all learning and team communication switched online. This led us to formulate the following research question:

> Does the increase in team dysfunctions, in the context of student team projects, come from the inadequacy of social media app communications functionalities to the kinds of teamwork modalities required by academic team projects?

Answering this question involved, among other things (see Chapter 2 and Section 7.1.2), using sentiment analysis techniques to diagnose team dysfunctions from traces of team communication, which involved training a machine learning model to recognize these functions in team communication. This, in turn, involved acquiring or building a dataset of team communications, labeled with team dysfunctions, which turned out to be a far more challenging–and interesting problem–than anticipated when I started this work.

The original research question remains to be answered. Based on the results of this thesis, we are reasonably confident that ChatGPT–or similar technologies–provides a viable methodology to generate the desired dataset, provided that we are able to improve the generation of the dialogues, and formally validate the quality of the generated dataset. The preliminary analysis of Chapter 3 provides the methodological foundation to answer the research question.

APPENDIX A
GENERATED DIALOGUES

A.1 Trust Dysfunction Dialogue Samples

A.1.1 Low-level Dialogue

Team Member 1: Hey, I noticed that the marketing team is overwhelmed with their workload. Maybe we should offer to help them out? Team Member 2: Hmm, I'm not sure if we should do that. I mean, it's not really our responsibility, right? Team Member 3: Yeah, I agree. Our focus should be on our own tasks and meeting our own deadlines. Team Member 1: But we're a team, and we should support each other. If we ease their workload, they'll be more productive, and it benefits the entire organization. Team Member 2: That might be true, but if we start helping other departments, where do we draw the line? We might end up taking on tasks that are outside of our expertise or that we are not equipped to handle. Team Member 3: Plus, if we step in and help too often, it might create a dependency on us, and everyone will expect us to solve their problems. Team Member 1: I see your concerns, but this seems like a temporary situation. The marketing team just needs some assistance right now. It won't become a regular occurrence if we make it clear that we are helping them as a one-time thing. Team Member 2: I understand your point, but I still don't feel comfortable going outside of my assigned responsibilities. I don't want to overstep boundaries. Team Member 3: I agree with Team Member 2. We should focus on excelling in our respective roles rather than taking on extra responsibilities. Team Member 1: Okay, I understand your reservations. I'll respect your decision. However, I still believe that as a team, we should be willing to lend a helping hand when it's necessary. I'll communicate that to the marketing team and let them know that our offer is on the table if they need it.

A.1.2 Medium-level Dialogue

Team Member 1: Hey, I've noticed something that's been bothering me. Do you mind if I bring it up? Team Member 2: Uh, sure. What's on your mind? Team Member 1: Well, I've been struggling a bit with this specific task assigned to me. I feel like I could use some help, but I don't want to bother anyone. Team Member 2: Oh, you shouldn't hesitate to ask for help. We're a team, after all. I'll be more than happy to assist you with whatever you need. Just let me know how I can help. Team Member 1: Thank you. I appreciate that. I was worried that I might come across as incapable or burdening others by asking for assistance. It's a relief to know you're willing to support me. Team Member 2: No problem at all. We're all here to contribute to the success of the team. Asking for help when needed is a sign of strength, not weakness. We all have our areas of expertise, and we can learn from each other. Team Member 1: That's true, and speaking of learning, I've noticed that you excel in another aspect of our project that I'm not entirely familiar with. I was wondering if you could share some insights and guidance with me? Team Member 2: Absolutely! I'd be more than happy to provide you with any information or guidance you need. Just let me know what specifically you'd like help with, and I'll gladly share my knowledge and experience with you. Team Member 1: That's great to hear. I appreciate your willingness to help. I believe learning from each other within the team will only make us stronger and more efficient in our roles. Team Member 2: I couldn't agree more. Constructive feedback and open communication are essential for our growth individually and as a team. We should always feel comfortable providing feedback and suggestions to help each other improve. Team Member 1: I completely agree, but sometimes I hesitate to give feedback because I don't want to come across as criticizing or overstepping boundaries. Team Member 2: I understand your concern, but as long as feedback is delivered with respect and in a constructive manner, it can be incredibly valuable. It's important for us to create an environment where we can openly exchange ideas and opinions without any fear or hesitation. Team Member 1: You're right. I'll make an effort to voice my feedback more often and in a manner that is both helpful and respectful. It's a promising step towards our team's growth and success. Team Member 2: Fantastic! I'm glad we had this conversation. Remember, we're here to support each other and help one another excel in our respective roles. So, never hesitate to ask for help or provide feedback. It's how we'll become a truly exceptional team.

A.1.3 High-level Dialogue

Team Leader (TL): Alright team, I'd like us to take a moment and reflect on our recent project. It's important for us to recognize our weaknesses and mistakes so that we can learn and improve.

Who would like to start? Team Member 1 (TM1): I'll go first. I admit that I made a mistake during the project's planning phase. I underestimated the amount of time required for certain tasks, causing our timelines to get delayed. I apologize for not considering all the factors properly. TL: Thank you, TM1. It takes courage to admit when we've miscalculated. Communication is essential, and I appreciate your honesty. Anyone else? Team Member 2 (TM2): I'd like to admit my weakness in communication. I tend to struggle with articulating my thoughts clearly, which resulted in misunderstandings amongst the team. I understand the importance of effective communication and working on it. TL: TM2, acknowledging this weakness is a great step towards improvement. We can work together to find ways to enhance your communication skills, such as team-building exercises and workshops. Is there anything specific you'd like to focus on? TM2: I believe I need to work on actively listening to others and asking for clarifications when needed. By doing so, I can make sure I understand others better and express my thoughts more clearly. TL: Those are excellent points, TM2. We'll create opportunities for you to practice active listening in our future team meetings. Your commitment to improving your communication skills is commendable. Team Member 3 (TM3): I'd like to admit my weakness in time management. During this project, I often found myself struggling to prioritize tasks and lost track of deadlines. This affected the overall productivity and caused unwanted stress for the team. TL: Thank you for voicing that, TM3. Acknowledging our weaknesses is crucial to growth. Let's explore strategies to help you better manage your time, such as implementing time-tracking tools, setting specific goals, or breaking down tasks into smaller, more manageable portions. We'll work together to find a method that suits your working style. Team Member 4 (TM4): I think I need to take responsibility for not speaking up when I noticed potential issues during the project. I didn't want to come across as interfering, but now I realize how important it is to voice concerns and suggestions so that the team can benefit. TL: TM4, your insight is valuable, and your willingness to take responsibility is commendable. It's crucial for open communication and active involvement within our team. Let's ensure that in future projects, we create an environment where everyone feels comfortable speaking up to address potential issues or provide suggestions for improvements. TL: As a team, we've made significant strides today by admitting our weaknesses and mistakes. It shows maturity and a spirit of continuous improvement. Now, let's work together to overcome these challenges and build a stronger, more successful team.

A.2 Conflict Dysfunction Dialogue Samples

A.2.1 Low-level Dialogue

Title: Unhealthy Team Environments: Nurturing Back-Channel Politics and Personal Attacks Characters: 1. Emily - Team Leader 2. Jessica - Team Member 1 3. Alex - Team Member 2 4. Matt - Team Member 3 5. Sarah - Team Member 4 Setting: A conference room during a team meeting — (Scene opens with Emily, Jessica, Alex, Matt, and Sarah already seated at the conference table, prepared for a team meeting.) Emily: Good morning, everyone! Let's start by discussing our progress on this project. Any updates or concerns to share? Jessica: Actually, Emily, I wanted to mention that I'm not entirely convinced of Alex's competence in this project. I often see inconsistencies in his work, which is impacting our team's overall efficiency. Alex: (defensively) Jessica, I don't appreciate you calling me out like this in front of everyone. If you have an issue, you could've brought it up privately. Sarah: (whispering to Matt) Did you notice how Jessica attacked Alex? This has been happening frequently, and it's breeding a toxic environment. Matt: Yeah, I've noticed that too, Sarah. But what concerns me even more is how Emily allows these personal attacks to fester. It undermines our team's unity and productivity. Emily: (attempting to address the situation) Hold on, everyone. Let's focus on discussing our concerns while being mindful of our tone and maintaining a respectful and collaborative environment. Jessica: (interrupting) Sorry, Emily, but I feel like my concerns deserve to be addressed publicly. Alex's careless mistakes are affecting all of us. Alex: (getting frustrated) Jessica, your constant criticism undermines team morale. Have you considered addressing your concerns directly with me rather than involve the entire team every time? Sarah: (nervously) Guys, we should find ways to resolve issues without making accusations or attacking one another. We're supposed to work as a team, remember? Emily: Sarah is right. We need to foster respectful communication and deal with personal disputes privately. Openly criticizing one another only leads to back-channel politics and division within our team. Matt: (supporting Sarah) I couldn't agree more, Emily. Encouraging open dialogue will help us build trust and create a healthier work environment where we can address any concerns constructively. Jessica: (reflecting) You're right, guys. I apologize for my tone and public critique, Alex. I should have discussed my concerns with you first. Alex: (calming down) I appreciate your acknowledgment, Jessica. Let's have a chat after the meeting to address these issues and find ways to improve our collective performance.

A.2.2 Medium-level Dialogue

Team Member 1: Hey everyone, I've been thinking about the way we collaborate as a team, and I feel like we could improve our communication and idea-sharing processes. Team Member 2: What do you have in mind? I think we're doing just fine. Team Member 3: Yeah, I agree. We're all pretty open about sharing our thoughts and suggestions. Team Member 1: While that may be true, I can't help but notice that sometimes we allow back-channel politics and personal attacks to creep into our discussions. It's not healthy for our team dynamic. Team Member 4: I've noticed that too, actually. Certain team members tend to undermine others instead of working together. Team Member 2: Hmm, I see what you mean. I guess we should work on addressing that issue. But how do we do that and still extract and exploit everyone's ideas effectively? Team Member 1: Great question. I think the first step is to establish clear ground rules for our discussions. We need to emphasize respectful and constructive communication, ensuring everyone's ideas are heard, regardless of hierarchy. Team Member 3: I completely agree. It's crucial that we create an environment where everyone feels comfortable sharing their thoughts, without fear of personal attacks or politicking. Team Member 4: I think transparency is also important. We should encourage open dialogue and discourage any private conversations that exclude team members. Team Member 2: That sounds fair. We should also make sure to actively listen to each other, take turns speaking, and give equal opportunity for everyone to voice their ideas. No interrupting or dominating the conversation. Team Member 1: Exactly. Additionally, we should implement a structured feedback system where we critique ideas, not individuals. Constructive feedback can help us refine and improve our collective work without resorting to personal attacks. Team Member 3: To further encourage idea extraction, we could also introduce brainstorming sessions where we explicitly focus on generating a wide range of ideas. This way, no team member will feel left out or silenced. Team Member 4: That's a great idea. We could even assign someone as a facilitator to ensure all ideas are thoroughly explored and discussed. Team Member 2: I like that suggestion. It would relieve some of the pressure and prevent any individual from dominating the conversation or dismissing others' ideas. Team Member 1: Agreed. And finally, creating a positive team culture with regular team-building activities can help us build trust and foster a collaborative environment where everyone feels comfortable sharing their ideas. Team Member 3: I think these initiatives would greatly benefit our team dynamic. By addressing the issues of back-channel politics and personal attacks head-on, we can create a space where everyone feels valued and heard. Team Member 2: Absolutely. Let's start implementing these changes and prioritize building a productive and inclusive environment.

A.2.3 High-level Dialogue

Team Member 1: Good morning, everyone! As our project kickoff meeting is coming up, I thought it would be beneficial for us to discuss how we can extract and exploit the ideas of all team members. Any thoughts or suggestions? Team Member 2: Great point! One way we can ensure that all ideas are heard is by implementing a brainstorming session during our meetings. We can create an open and non-judgmental environment where everyone feels comfortable sharing their thoughts. Team Member 3: I agree with that. Additionally, we can encourage active participation from everyone by using techniques like round-robin brainstorming. This way, each member can contribute one idea at a time, making sure nobody's input is overlooked or overshadowed. Team Member 4: I think it would be helpful to assign a designated moderator for each meeting. This person will ensure that everyone has an equal opportunity to speak and that ideas are properly explored and debated. Team Member 1: That's a great suggestion. It's important to have someone guiding the conversation, so no ideas go unnoticed. Additionally, we can leverage technology tools such as collaboration software, where team members can share and discuss their ideas digitally. This ensures that even the quieter team members have a platform to contribute. Team Member 2: Absolutely. And during these discussions, we should actively listen to each other's ideas without interrupting or dismissing them. Respectful communication and active listening will create an environment where team members feel valued, leading to inclusive and diverse ideas. Team Member 3: Another approach we can use is the 'nominal group technique.' Here, each member writes down their ideas individually, then we compile them without revealing who contributed what. This helps eliminate biases and encourages honest and unbiased evaluation of all ideas. Team Member 4: I love that idea! It will ensure that ideas are selected based on their merit, rather than personal preferences or influences. And once we select the best ideas, we can create sub-teams to further explore and develop those concepts, allowing everyone to participate actively. Team Member 1: Excellent suggestion! By dividing into smaller teams, we can ensure that every team member's skills and expertise are put to use. It also gives us an opportunity to continuously refine and build upon the ideas, making them even stronger. Team Member 2: Lastly, to ensure that our team members feel appreciated and motivated to share their ideas, we should celebrate and recognize their contributions. Whether big or small, acknowledging each member's input will foster a collaborative culture of idea extraction and exploitation. Team Member 3: I completely agree. Recognizing and appreciating everyone's contributions will not only boost morale but also encourage them to continue sharing their ideas, leading to even greater success for our team. Team Member 4: Let's make sure to implement these strategies during our upcoming kickoff meeting and throughout the project. By extracting and exploiting the ideas of all team members, we can create innovative solutions and achieve outstanding results. Together, we can accomplish anything!

A.3 Commitment Dysfunction Dialogue Samples

A.3.1 Low-level Dialogue

Team member 1: Alright everyone, we need to discuss the budget allocation for our upcoming project. We've already gone through this multiple times, but it seems like we still can't reach a consensus. Can we please focus and make a final decision today? Team member 2: I know we've discussed this before, but I still have some concerns about having such a large portion of the budget allocated to marketing. Shouldn't we invest more in research and development instead? Team member 3: We've already addressed this concern, and we agreed that the marketing department needs additional funding to ensure a successful product launch. We can't afford to skimp on marketing efforts. Team member 2: I understand the importance of marketing, but I think we should reconsider. Perhaps we can find a middle ground that allows for increased investment in both research and development and marketing. Team member 4: We've had this exact conversation three times already, and I'm getting frustrated. We've weighed the pros and cons, and the decision was made to prioritize marketing. Reopening this discussion won't change anything. Team member 1: I do empathize with your concerns, but as team leader, we need to keep the project moving forward. We have already spent a significant amount of time in this discussion, and revisiting it repeatedly will only delay our progress. Team member 2: I understand your point, but I still believe it's necessary to reevaluate our options. We need to ensure that all aspects of the project are adequately funded and receive the attention they deserve. Team member 3: I think it's important for us to trust the decisions we've already made and focus on executing the plan. We can always revisit the allocation in our post-project analysis and make adjustments for future projects. Team member 4: Exactly! We need to move forward and trust in the expertise of our team. We've discussed this enough, and it's time to finalize the budget and start working towards our goals. Team member 1: I appreciate everyone's input, and while it's important to reconsider decisions, we also need to strike a balance between efficiency and perfection. In the interest of progress, let's put this discussion to rest and move on to the next agenda item.

A.3.2 Medium-level Dialogue

Team member 1: Hey everyone, I've been thinking about our project and I believe we should focus more on improving the interface design for our application. It's crucial to provide an excellent user experience. Team member 2: That's a valid point, but we should also consider enhancing the functionality and adding new features. We need to make sure our application is robust enough. Team member 3: I agree with both of you, but we mustn't forget about optimizing the application's performance. Users won't stick around if it's slow and inefficient. Team member 4: While I understand the importance of all these aspects, we must prioritize security. Our users need to feel confident that their data is safe within our app. Team member 1: Absolutely, we can't neglect security. However, if we invest too much in security, we might sacrifice the user experience. Team member 2: But if we prioritize functionality and new features over everything else, we risk launching a potentially unstable and unattractive product. Team member 3: Hold on, shouldn't we gather user feedback and preferences first? It might help us align our priorities based on user orientation. Team member 4: True, user preferences should guide our decisions. Nonetheless, we can't ignore the technical aspects that ensure our app's longevity and credibility. Team member 1: Maybe we could conduct a survey or focus groups to determine our users' expectations around security, user experience, functionality, and performance. That way, we could have a clearer picture of their preferences. Team member 2: That's a great idea. By involving users in the decision-making process, we can ensure we're addressing their concerns and providing them with what they truly value in our application. Team member 3: Agreed. This approach would help us avoid ambiguity among the team while also obtaining valuable insights to prioritize our efforts effectively. Team member 4: I'm glad we could find common ground. Involving users and aligning their preferences with technical requirements will lead us towards a successful project outcome.

A.3.3 High-level Dialogue

Team member 1: Hey everyone, I think we need to have a discussion about our direction and priorities moving forward. Lately, it seems like we have been working on multiple tasks without a clear focus. This has led to confusion and a lack of progress. Team member 2: I completely agree. It's essential for us to align and understand where we are heading as a team. Can we start by discussing our overall goals? Team member 3: That sounds like a good starting point. So, our main goal is to increase customer satisfaction, right? Team member 4: Yes, that's correct. And to achieve that, we need to improve our response time to customer inquiries and clarify our product features. Team member 1: Agreed. Customer satisfaction should be our top priority, but let's break it down into smaller, actionable steps. How about if we prioritize enhancing our customer service platform first and then move on to refining our product features? Team member 2: That sounds reasonable. By focusing on customer service initially, we can ensure that we have a strong foundation to provide accurate and timely support. That will contribute to increasing customer satisfaction. Team member 3: I like the idea of breaking it down into smaller steps. It's easier to focus on one aspect at a time rather than trying to tackle everything simultaneously. Team member 4: Definitely. And once we have our customer service platform optimized, we can then concentrate on improving our product features to align with customer preferences and needs. Team member 1: Great. So we have established that our immediate priority is to streamline our customer service platform. What specific actions do we need to take to achieve this? Team member 2: I suggest conducting a thorough analysis of our current customer service process to identify any bottlenecks or areas for improvement. Team member 3: Additionally, we should invest in training and development programs for our customer service team to enhance their skills and ensure they provide exemplary support. Team member 4: I agree. It would also be helpful to implement a feedback system where customers can rate their experience with our support team to track our progress. Team member 1: These are all excellent suggestions. Let's put them into action and designate team members responsible for each task. This way, we can ensure accountability and efficient execution. Team member 2: Absolutely. Clear roles and responsibilities will enable us to move forward with clarity and focus on achieving our goals. Team member 3: It's reassuring to have this clarity now. I believe with this direction and prioritization, we'll be able to significantly improve customer satisfaction. Team member 4: I'm glad we had this discussion. With a clear path and priorities, we can now work together towards our shared goal effectively. By engaging in this dialogue, the team members were able to create clarity around their direction and prioritize their actions to achieve their primary goal of increasing customer satisfaction. This discussion ensured that everyone was on the same page and understood their roles and responsibilities, leading to a more focused and efficient team.

A.4 Accountability Dysfunction Dialogue Samples

A.4.1 Low-level Dialogue

Team Member A: Hey everyone, I have an idea for improving our overall performance and meeting our targets faster. I suggest we should set higher performance standards for ourselves. Team Member B: Whoa, hold on a second. I understand that we all want to excel, but isn't that a bit unrealistic? We should make sure our goals are attainable and don't put unnecessary pressure on ourselves. Team Member C: I agree with B here. We might already be working at our maximum capacity, and adding more expectations could lead to burnout. It's crucial to find a balance that can keep our motivation high without sacrificing our well-being. Team Member A: I get where you're coming from, but I disagree. We won't know our true potential unless we push ourselves beyond our comfort zones. If we don't aim high, we won't achieve extraordinary results. We're capable of exceeding our current standards if we put in the effort. Team Member B: I understand your perspective, A, but not everyone has the same abilities or circumstances. We may have team members with different skill sets or personal commitments outside of work that limit their available time. Imposing higher standards could create an unfair expectation for them. Team Member C: Precisely. We need to value the diverse skills and contributions of every team member, rather than disregarding their efforts based on a homogeneous performance standard. It's not fair to compare individuals with different backgrounds and resources. Team Member A: Okay, but if we lower our standards to accommodate everyone's capabilities and circumstances, won't that hinder our growth as a team? We'll never reach our fullest potential if we settle for mediocrity. Team Member B: It's not about settling for mediocrity. It's about being realistic and recognizing that everyone has their limits. We can still challenge ourselves and strive for improvement while appreciating each team member's unique strengths. Team Member C: Exactly. A supportive and inclusive team environment is crucial for long-term success. Instead of setting higher standards that may create resentment and feelings of inadequacy among team members, let's focus on effective communication, collaboration, and leveraging our individual strengths. Team Member A: I see your points, but I still believe having higher standards can push us to achieve great things. How about we come up with a compromise? We establish ambitious goals but provide additional support and resources for those who need it, ensuring individual growth opportunities and fair assessments.

A.4.2 Medium-level Dialogue

Team Member A: Hey everyone, I wanted to address something that's been bothering me lately. It seems like some of us have different performance standards, and I think it's creating resentment among the team. Team Member B: Really? I haven't noticed anything out of the ordinary. Can you give us an example? Team Member A: Well, for instance, during our last project, some team members consistently slacked off and didn't put in the same level of effort as others. It made me feel like my hard work was being taken for granted. Team Member C: I can understand how that might make you feel frustrated, but I think sometimes people have different capacities or challenges that we may not be aware of. Team Member D: I agree with Team Member C. We don't always know what's going on in someone's personal life or what hurdles they might be facing. It's important to remember that everyone has their own pace and circumstances. Team Member A: I understand that, but when some members consistently underperform, it affects the overall team's performance and outcomes. It makes it harder for us to accomplish our goals efficiently. Team Member B: That's a valid concern, Team Member A. Maybe we can find a way to address this issue without causing more division within the team. Team Member C: How about setting some performance expectations or goals as a team? We can establish a minimum standard that everyone should meet. Team Member D: Yes, that's a good idea. By setting clear expectations, we'll create a sense of accountability for each team member. It will also help those who are struggling to understand what is expected of them. Team Member A: I like that suggestion. If we have a collective understanding of what is considered acceptable performance, it could create a positive pressure for those who are falling behind to improve and keep up with the rest of the team. Team Member B: I think that's a fair solution. It ensures that everyone is on the same page, and it shows that we genuinely care about each person's growth and development. Team Member C: Additionally, we should also provide support and resources to those who are struggling. Maybe organizing some training sessions or mentorship opportunities could help them improve their performance. Team Member D: Absolutely. It's vital that we foster an environment where everyone feels supported and motivated to do their best. By addressing this issue and finding constructive solutions, we can build a stronger and more cohesive team. Team Member A: I appreciate your understanding and willingness to tackle this matter together. I think by implementing these suggestions, we will be able to improve our team dynamic and performance while ensuring nobody feels left behind. Team Member B: Agreed. Let's take concrete steps towards creating a better work environment for everyone.

A.4.3 High-level Dialogue

Team member 1: Hey everyone, I wanted to discuss something important with all of you. Lately, there have been some concerns raised about certain team members who have been consistently underperforming. It's affecting our overall team's productivity, and we need to address this issue. Team member 2: I agree. It's crucial for our team's success that we hold each other accountable and maintain high standards. We need to ensure that everyone understands the importance of their contribution. Team member 3: I think it's essential to approach this issue with empathy and understanding. Instead of singling out poor performers and making them feel isolated, we should collectively motivate and encourage them to improve. Maybe they're facing challenges we aren't aware of. Team member 1: Absolutely, Team member 3. We don't want anyone to feel demoralized or humiliated. It's important to approach this conversation with sensitivity, emphasizing that we believe in their potential for growth and their ability to make a significant contribution to the team. Team member 4: I think setting clear expectations and goals can also help poor performers feel pressure to improve. If they understand what is expected of them, and the impact their performance has on the whole team, it might push them to make necessary changes. Team member 2: That's a great point, Team member 4. Giving feedback regularly, both positive and constructive, can also make a big difference. By highlighting their strengths and areas for improvement, we show them that we value their contribution while also making it clear there's room for growth. Team member 3: Additionally, it might be useful to offer support and resources to help them enhance their skills. Providing mentorship or suggesting training opportunities can demonstrate that we're invested in their development. They might just need guidance to overcome their challenges. Team member 1: Agreed. By taking this approach, we create a culture of continuous improvement and support, where team members feel accountable for their own performance, but also feel comfortable asking for help when needed. It's all about fostering a collaborative environment. Team member 4: Exactly. Let's remember that our aim is not to punish or isolate poor performers, but to help them unleash their full potential. Our collective success depends on the growth of each individual member. Team member 2: Well said, Team member 4. It's essential that we all commit to this approach and hold ourselves accountable. With teamwork and support, we can ensure that every team member feels the pressure to improve and contribute their best. Team member 3: Agreed. Together, we can create an environment where everyone strives for excellence, helping our team reach new heights. Let's support each other and make sure we're empowering our colleagues to grow. Team member 1: That's the spirit! Thank you all for your insights and commitment to building a high-performing team. Let's put these ideas into action and see the positive impact it has on our team's overall performance.

A.5 Results Dysfunction Dialogue Samples

A.5.1 Low-level Dialogue

Team Member 1: Hey everyone, I wanted to take a moment to talk about something important. As a team, we've always emphasized collective success and achieving our goals together. But I believe it's equally important to support each other's individual career aspirations and personal goals. Team Member 2: I completely agree. Each one of us has our own unique talents, interests, and dreams. It's essential that we acknowledge and nurture those aspirations alongside our team goals. Team Member 3: Absolutely! Encouraging personal growth and individual goals not only helps our team members flourish but also benefits the team as a whole. When we pursue our own passions, we bring fresh perspectives, new skills, and innovative ideas to the table. Team Member 4: I see what you mean, but sometimes it can be challenging to balance our personal goals with the demands of our team responsibilities. How can we manage both effectively? Team Member 1: That's a great point. It's all about finding the right balance. We can start by openly communicating about our personal aspirations with each other. By sharing our individual career goals and passions, we can gain valuable insights and support from one another. Team Member 2: Additionally, we should encourage continuous learning and professional development. Whether it's attending workshops, taking courses, or seeking mentors, investing in ourselves benefits both us as individuals and the team. Team Member 3: I agree, and it's important for us as a team to promote a culture that values personal growth. Let's create an environment where team members feel comfortable discussing their individual goals and seek help from others. Team Member 4: I really appreciate these suggestions. It's reassuring to know that our team believes in personal growth and supports each other's career aspirations. I will definitely take advantage of the opportunities to learn and develop myself further. Team Member 1: That's great to hear! Remember, by focusing on our individual goals, we enhance our abilities, reach new heights in our careers, and contribute even more to the team's success. Team Member 2: Exactly! When we have a team of people striving towards their own goals, it fosters a sense of motivation, drive, and innovation. Each person brings a unique perspective and skill set, which ultimately elevates the team's performance. Team Member 3: So let's encourage one another, celebrate personal achievements, and provide support when needed. We are a team that values both collective success and individual growth.

A.5.2 Medium-level Dialogue

Team Leader (TL): Good morning, team. I've observed a recurring issue within our group that I believe we need to address. It seems that some team members are more focused on individual or departmental recognition and their egos rather than the collective goals of our team. We need to discuss this and work towards a solution. Team Member 1 (TM1): I think individual recognition is vital. After all, I came up with the idea that brought in that big client last month, and I deserve credit for it. Team Member 2 (TM2): I agree with TM1. My department has been consistently outperforming others, and it's essential that we get recognized for our hard work. Team Leader: I understand the desire for recognition, and I appreciate your individual and departmental contributions. However, we must remember that we're a team, and our primary objective is to achieve success together. Focusing solely on individual and departmental recognition can compromise our unity and hinder collaboration. Team Member 3 (TM3): But sometimes, when we emphasize the team's success, it feels like our individual efforts go unnoticed. Team Member 4 (TM4): Exactly, TM3. It's disheartening to feel like our achievements aren't being acknowledged. Team Leader: I acknowledge your concerns, TM3 and TM4. But it's essential to strike a balance between individual recognition and team success. Our individual successes should contribute positively to the overall team performance. When the team succeeds, it ultimately benefits all of us, including individual career growth. Team Member 5 (TM5): We are here to advance our careers, and personal recognition is a significant part of that. Team Member 6 (TM6): I have to agree with TM5. My career development is a priority, and personal achievements matter a lot. Team Leader: I understand your career aspirations, and I support your individual growth. However, we need to remember that our collective success can open up more opportunities for everyone. It can also strengthen our department's reputation and create a more supportive working environment. Team Member 7 (TM7): Perhaps we need to strike a balance between individual recognition and team success. Let's ensure that everyone's achievements, whether individual or departmental, are acknowledged and celebrated. Team Leader: That's a good suggestion, TM7. We'll work on finding that balance and improving our communication and recognition processes. Our success as a team can coexist with individual and departmental recognition. It's crucial to foster a culture where we all thrive and contribute to our shared goals.

A.5.3 High-level Dialogue

Setting: A conference room at a technology company. Team members are discussing the development of a new software project. Team Leader: Alright, everyone, let's start this meeting. We have a challenging project ahead, and I want to discuss how we can achieve the best possible results. One thing I've noticed is that sometimes individuals need to subjugate their own goals or interests for the good of the team. Does anyone have any thoughts on this? Sarah: Well, I think it's crucial for us to understand that sometimes sacrifice is necessary for the greater good of the team. In a collaborative project like this, we need to work together and prioritize the team's needs over our personal goals. John: I completely agree, Sarah. I think it's important to recognize that each team member brings unique skills and expertise to the table. By subjugating our personal interests and acknowledging the expertise of others, we can achieve more effective outcomes. Emily: I couldn't agree more. Collaboration and unity are key to success. When we suppress our individual goals and choose to focus on what's best for the team, we foster an environment of trust and support. It allows us to benefit from diverse perspectives and ultimately enhances the quality of our work. Team Leader: That's an excellent point, Emily. When team members put the project's success above personal ambition, it promotes a culture of shared responsibility and cooperation. It enables us to pool our talents, identify areas where others excel, and rally around achieving common goals. Michael: Absolutely, Team Leader. I've experienced firsthand how subjugating my own interests for the team's benefit leads to better outcomes. Sometimes it means taking on tasks that might not align with my expertise, but by doing so, it supports the team's progress and overall success. Sarah: That's true, Michael. Subjugating our goals doesn't mean we lose ourselves in the process, but rather, we make strategic and selfless decisions for the good of the team. It's about understanding that our collective achievements are the result of everyone working towards a common objective. John: And it's important to remember that this is a two-way street. When team members see others making sacrifices and subjugating their goals, it motivates us to reciprocate. It fosters an atmosphere of mutual respect and aids in building strong relationships among team members. Emily: Absolutely, John. It's about creating a positive cycle where we uplift and inspire each other through selflessness and collaboration. By subjugating personal goals in favor of the team, we strive towards achieving our shared vision with increased efficiency and effectiveness. Team Leader: Well said, everyone. It's clear that when individuals willingly subjugate their own goals for the betterment of the team, it can lead to outstanding results. Let's continue to foster this mindset as we work together on this project. I'm confident that our collective efforts will bring about success. Sarah: Agreed, Team Leader. With a team that prioritizes unity, collaboration, and the team's good over individual interests, we're well on our way to completing this project with excellence. John: Absolutely, let's remain committed to the team's success above all else. Our collective synergy will ensure we achieve remarkable outcomes.

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