The Effects of Stress and Chatbot Services Usage on Customer Intention for Purchase on E-Commerce Sites

by

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DECLARATION

I, Abed Matini, declare that the contents of this thesis represent my own unaided work and that the thesis has not previously been submitted for academic examination towards any qualification. Furthermore, it represents my own opinions and not necessarily those of the Cape Peninsula University of Technology.

31 January 2023

Signed Date

ABSTRACT

The customer relationship is an inevitable part of the growth of a business. Customer services companies have shown a major interest in integrating Artificial Intelligence (AI) into their systems. A chatbot is an AI app that can commence a conversational session with a human partner, maintain, and handle a twisted and complicated conversation in a natural language. The main reason that businesses are interested in chatbots is that they have found chatbots as a solution to reducing customer service costs as well as having the capability of handling multiple users simultaneously.

Investigations on recorded chats can lead companies to comprehend the contexts of messages, whether inquiries are informational or emotional. Therefore, sifting through messages can reveal “What is being said?”, “Was it positive or negative?”, “Was the customer angry, happy, frustrated, stressed, etc?”. Previous research indicates that some emotions are more relevant in marketing, such as anger, which shows that the customer is active and has an optimistic view of the future, therefore, it is more likely to lead to action.

The aim of this research is to power chatbots with algorithms that can determine a potential buyer from customers’ chats to offer them a sale. To reach our goal, detecting the potential customer from the chat is the main challenge that we have to overcome. Discovering emotions from chat will direct us to understand more about customers’ intention to purchase or accept an offer.

Experimental (empirical) research is defined as data-based research which relays on experiments or observations. Moreover, in experimental research, a verifiable conclusion should be generated by the researcher. Therefore, we developed a hypothesis and established an experimental design to prove or disprove it.

The Null Hypothesis (H0): There is no relation between user emotion to their online buying decision-making.

The Alternative Hypothesis (H1): User emotions play a significant role in online purchasing decision-making.

To prove or disprove this hypothesis, experimental research with a positive approach has been designed. The goal of this experimental research is to find out whether there is a relation between users’ emotions and their purchasing decision-making process. We found four datasets that are labelled with emotion tags and then filtered them based on the conversation about purchasing (both accepting and declining purchases).

The first dataset is called EmotionLines which is about Friends TV Series and has each utterance labelled by relevant emotions. The second dataset is called CARER which is generated from tweets from Twitter, labelled based on Emotional Hashtags. The third dataset is called GoEmotions which built its dataset manually and contains 58K Reddit comments labelled. The fourth dataset is called EmotionPush which is more than 8K messages from Facebook Messenger, manually labelled with relevant emotions. Based on the four datasets (EmotionLines, CARER, GoEmotions and EmotionPush) we filter the sentences that have mentioned purchase and diagrams have been generated for each dataset.

The result obtained doesn't show a clear relation between any particular emotion or stress to purchase. However, Joy and Neutral emotions still have the highest number of purchases. Our hypothesis testing also support our findings and we had to reject the alternative hypothesis.

Keywords: Chatbot, Emotion, Stress, Feelings, Customer Service, Compulsive Buyers, Microblog.

GLOSSARY

Terms/Acronyms/Abbreviations	Definition/Explanations
SLR	Systematic Literature Review
SLRQ	Systematic Literature Review Question

Table of Contents

List of Figures

List of Tables

CHAPTER ONE: Introduction

This chapter starts with an introduction to our research in Section 1.1, afterwards a description of the research background and motivation for this study in Section 1.2, and then the research problem is listed in Section 1.3. Section 1.4 presents the research aim and objective. The hypothesis development of this research is outlined in Section 1.5 and Section 1.6 discusses a proposed methodology for this research. Our theoretical, practical and methodological contributions are noted in Section 1.7. Section 1.8 focuses on the significance of the study. Section 1.9 ends this chapter with a descriptive structure of the thesis.

1.1 Introduction

The customer relationship is an inevitable part of the growth of a business. Customer services companies have shown a major interest in integrating Artificial Intelligence (AI) into their systems. AI includes a diverse range of human behaviour which can be apprehended by a system. Behaviours such as emotion, recognition, and learning (Li & Du, 2017).

Recent advancements in AI and data analytics power computers to comprehend unstructured data, in the form of plain text, audio, images and videos. Some independent researchers predicted that two-thirds of inquiries in customer service would be handled by AI systems in the near future (Khan & Das, 2017). Chatbots, known as intelligent chat agents are one of the kinds of AI systems that we discuss it in this research. A chatbot is an AI app that has the ability to commence a conversational session with a human partner, maintain and handle a twisted and complicated conversation in a natural language (Argal et al., 2018).

Georgescu (2018) indicates that over 11,000 chatbots have been developed on Facebook Messenger and anticipate that 80% of businesses will involve chatbots on their communication systems by 2020. The main reason that businesses are interested in chatbots is that they have found chatbots as a solution to reducing customer service costs as well as having the capability of handling multiple users simultaneously (Ranoliya et al., 2017). In addition, chatbots' capability to access and process to an enormous amount of data to suggest or recommend a solution would enhance customer experience (Sahaja et al., 2019).

Moreover, customer services companies send and receive messages via text and phone on an immense scale daily. Some companies record these messages for further investigating, training, and quality measuring purposes. These investigations can lead companies to comprehend the contexts of messages, whether inquiries are informational or emotional. Therefore, sifting through messages can reveal “What is being said?”, “Was it positive or negative?”, “Was the customer angry, happy, frustrated, stressed, etc?”. Finding out customers’ opinions and private states, such as beliefs, feelings and emotions, is in the Sentiment Analysis domain (Mohammad & Turney, 2013).

Sentimental Analysis contributes to finding out users’ feelings while interacting with a chatbot or if human intervention is needed in order to respond to the inquiries. Moreover, sentimental analysis can determine when the best time is to suggest an offer to the user (Chintalapudi et al., 2018). Sentimental Analysis analyse people’s opinions, feelings, and emotions towards products or services from a written language (Liu, 2012). Sentimental analysis can also indicate the sentence intention whether is a positive, negative or neutral. This is extremely helpful for companies to find out clients’ overall opinion about a product or service (Ramanathan & Meyyappan, 2019).

Emotion detection in Human-Computer Interaction (HCI) has been researched for more than two decades (Kaiser & Oertel, 2006). Picard (1999) mentioned the importance of emotions that are hidden in the texts. Emotion detection is an imperative part of a chatbot, which enables the chatbot to detect the emotional state of the user and respond to it accordingly. There are diverse ways of labelling a user’s emotional states. For example, Fadhil (2018) suggested dividing the emotional state into three categories namely Optimistic, Pessimistic and Moody feelings.

Plutchik (1980) categorised emotions into eight basic types, they are joy, fear, sadness, trust, anger, surprise, disgust and anticipation. Seyeditabari et al. (2018) indicate some emotions are more relevant in marketing, such as anger, which shows that the customer is active and has an optimistic view of future, therefore, it is more likely to lead to action. Furthermore, emotion detection can analyse clients’ reaction to a product in order to improve the relationship with the customer. Thus, understanding emotions and their importance in the human decision-making process would profit any commercial entities, institutes, and organizations.

1.2 Background

The aim of this research is to power chatbots with algorithms that can determine a potential buyer from customers' chats to offer them a sale. In order to meet our aim, detecting the potential customer from chat is the main challenge that we have to overcome. Discovering emotions from chat will direct us to understand more about customers' intention to purchase or accept an offer.

1.2.1 Emotions

Dawson et al. (1990) mentioned that the tendency to purchase retails is variable and it depends on a customer's emotion or mood. Xu et al. (2017) showed that customer inquiries are either Informational or Emotional. They have found that over 40% of inquiries are emotional. In this research, we are focusing on the emotional section of the inquiries and discovering users' emotional states from chat. Firdaus et al. (2018) reference several research undertakings that have been conducted to realize human emotions through a person's written content. Emotion detection has been applied to novels, emails, news headlines, suicide notes and Twitter previously (Roberts et al., 2012). However, more research remains to be conducted on chatbot customer services and users.

Seyeditabari et al. (2018) indicate three main open problems influencing detecting expressed emotions from the text:

1. **The multiplicity of emotions expressed by humans in brief phrases.** A brief sentence may carry many emotions. Moreover, the complexity of emotional language as well as context dependency of emotions in sentences, which increase the difficulty of finding the implicit emotions in contexts;
2. **Shortage of qualitative and quantitative data,** which affects the classification of an algorithm's performance, whether this classification is using a Supervised or Unsupervised model. For using a supervised model, a large amount of annotated data is required;
3. **Insufficiency in emotion classifier models,** which results in classifiers being limited to main emotions only, i.e. classify any emotion (Anger or Not Anger) or classify for a pair of emotions (Joy vs Sadness) (Krishnan et al., 2017).

In this research, we are going to focus more on finding supervised or unsupervised algorithms, which require less amount of data for training, in order to cover the Shortage of

Data in chatbots. Furthermore, we will discuss more detecting emotions (such as stress and anxiety) in a chat session, which leads customers to make a purchase.

1.2.2 Stress and Anxiety in Compulsive Shoppers

Compulsive shoppers do shopping as a quick solution to alleviate negative feelings of stress and anxiety. Moreover, compulsive consumers are less concerned about the reason for buying and measure the positive feeling generated by purchasing items more (Edwards, 1993). A research study shows that compulsive shoppers who have difficulty controlling their purchases could be also a great target to suggest a sale to (Valence et al., 1988). They are addicted to shopping and make procurements repeatedly (Saraneva & Sääksjärvi, 2008). In this research, we focus on determining compulsive shoppers by focusing on detecting stress from chat and suggest sales to them.

1.2.2.1 Stress Detection Algorithms

There have been several research projects about detecting emotions from Tweets (Roberts et al., 2012; Bravo-Marquez et al., 2016; Krishnan et al.,2017; Firdaus et al., 2018). They have applied classifiers, prediction and detection algorithms for detecting emotions from Tweets. Furthermore, more specifically, there is research about detecting stress from Tweets recently (Lin et al., 2014; Pillai et al., 2018; Ali et al., 2018). They also have applied classifiers, detection algorithms as well as predefined rules and deep neural network to detect stress on Twitter.

Roberts et al. (2012) mentioned two advantages to using microblogs (such as Tweets); algorithms compare to other textual algorithms to utilize for our chatbot stress detection research. First, microblogs are restricted to a number of characters. Therefore, users are forced to express their thoughts in brief sentences, which has a similarity to chat sessions. Second, users Tweet more frequently compared to posting on other social media websites or sending emails. Thus, microblogs have more real-time content compared to other contextual sources. Geng et al. (2019) indicated another microblogging advantage which is the capability of mirroring public opinion compare with traditional clustering algorithms.

Since supervised and unsupervised learning algorithms have been used for microblogging websites, such as Twitter for detecting emotions and specifically stress from Tweets. We are going to redesign those algorithms to work on a setup text messages that come as a chat from the user so as to obtain our data set for the experiment and find out who can be a potential buyer and to offer them sales.

1.2.3 Potential Buyer and Compulsive Buyer Detection Model

The flowchart below in Figure 1.1 shows the two major tasks of the Potential Buyer Detection Model. The first task is to apply stress detection algorithms to process every single word of the chat and determine if the user is stressed or not.

The second task is to check the history of the user if it exists and to find out if the user has accepted or rejected any sales offers before while they were stressed. If both conditions are positive, the customer's data would be detected and stored in the database as a potential buyer and compulsive buyer for future sales.

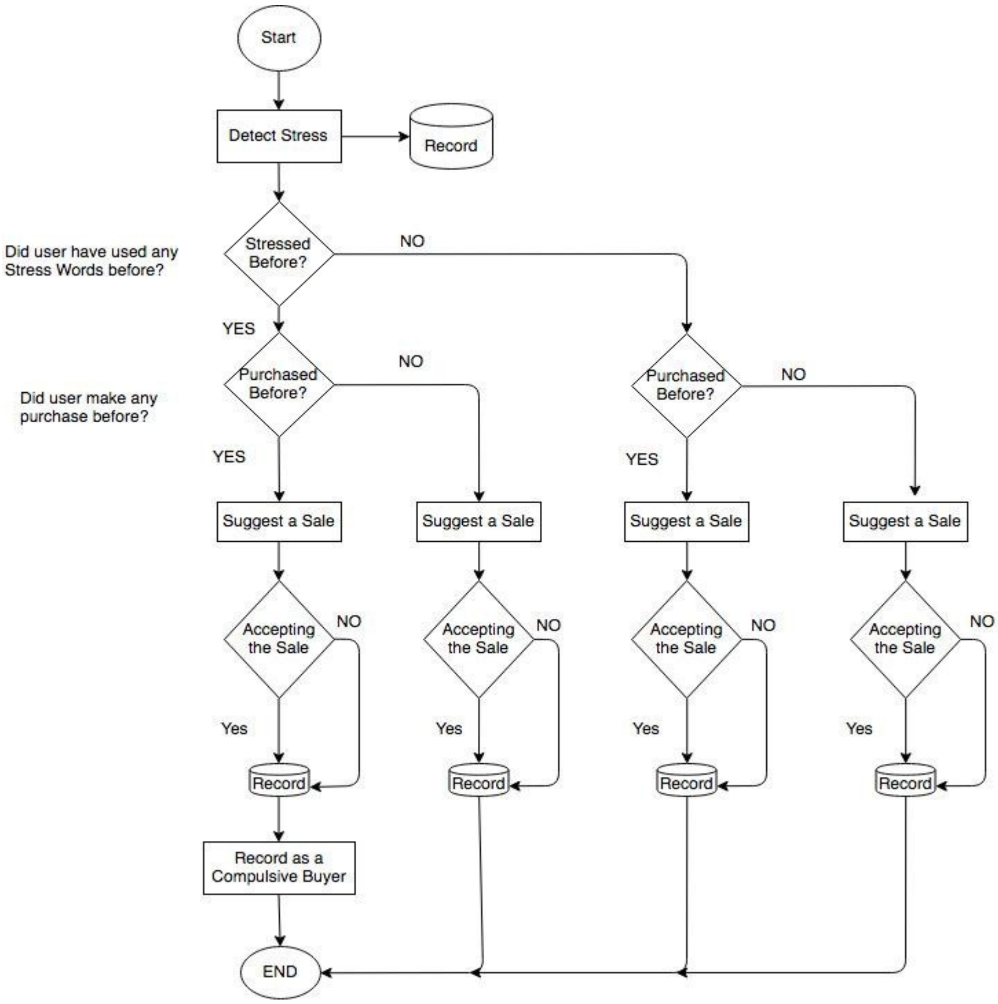


Figure 1.1 Flowcharts of Potential Buyer Detection Model

1.2.4 Related Research

Chen et al. (2018), published an article named Emotion Lines and generated an Emotion Corpus of conversations. They chose scripts of a TV show called Friends and labelled all utterances in it with Ekman's six basic emotions, anger, disgust, fear, happiness, sadness, surprise and neutral (if the emotion is not any of six mentioned emotions). The reason to choose a TV show script was availability of the scripts in the internet and similarity of TV shows' scripts to social dialogs with a chatbot.

In figure 1.2 we demonstrate an emotion detection scenario. There are patterns to detect and predefined templates to respond.

[[{ "speaker": "Rachel",
"utterance": "Everything's ruined. My bed. My clothes. Look at my favourite blue sweater.",
"emotion": "sadness",
"annotation": "0050000"
},{
"speaker": "Ross",
"utterance": "Do you have a minute? I'd like to talk to you about something I'm, I'm really uncomfortable talking about.",
"emotion": "fear",
"annotation": "1004000"
},{
"speaker": "Joey",
"utterance": "Really? A purse?",
"emotion": "surprise",
"annotation": "0000050"
}]]

Figure 1.2 Different emotions from Friends TV scripts

1.2.5 Summary of Background to the Research Problem

The challenge is to find out potential buyers from a chatbot session. There are users who are corresponding with chatbots frequently. There are two major data sets to analyse, as a solution, to find out whether a user can be a potential buyer or not. Either detect it from users' requests and questions about specific products (informational inquiries) or detect customer's emotional states during the open session (emotional inquiries) (Xu et al., 2017).

There are emotions, whether positive or negative, that can put users in specific emotional states so as to be less critical about a sales offer and consider that offer in a natural manner of the decision-making process (Seyeditabari et al., 2018). From all positive and negative feelings and emotions that influence users' decision-making processes, we chose stress and anxiety. There are three reasons to choose this:

1. Availability of solid and successful research about emotion detection and, specifically, stress detection from microblogs such as Tweets on social media

websites such as Twitter (Roberts et al., 2012; Lin et al., 2014; Bravo-Marquez et al., 2016; Krishnan et al.,2017; Pillai et al., 2018; Ali et al., 2018; Firdaus et al., 2018);
2. Availability of psychological research about the topic of compulsive buyers', which shows stress and anxiety as a trigger for shopping (Valence et al., 1988; Edwards, 1993);
3. The similarity of microblogging's context to chat (limitation in the number of characters and frequently posting on social media).

In this research we use the emotion labelled TV show scripts as dataset for our chatbot.

1.3 Problem Statement

The rapid growth of companies' interest to utilise chatbots in their companies' customer service section (Georgescu, 2018) and high expectations from chatbots to handle customers' requests in a comprehensive way (Zamora, 2017) push chatbot developers to enhance chatbot performance. Despite all of the progress and attempts at improving chatbot efficiency at detecting information, analysing and responding to users, emotion detection and, more specifically, stress detection, is missing from e-commerce chatbots. Whereas, Seyeditabari et al. (2018) indicate that some emotions contribute towards the decision making the process for purchase. Applying stress detection algorithms helps to power chatbots to perceive both explicit and implicit information from users. Lack of detecting emotions from e-commerce chatbots may affect the rate of users' engagement with chatbots.

1.4 Aim and Objectives

The aim of this research is to detect and classify potential buyers via automated chatbots so as to be able to put up an offer at a moment that would entice them to buy.

1.4.1 Objectives

1- Find datasets that have been labelled by emotions;
2- Identify the sentences or utterances that have mentioned buy/purchase or show intention to purchase;
3- Check the emotion that is associated with that sentence and create histograms based on that result.

1.5 Hypothesis

Kothari (2004), defined experimental (empirical) research as a data-based research which relay on experiments or observations. Moreover, he mentioned that in experimental research, a verifiable conclusion should be generated by researcher. Therefore, we developed a hypothesis below and will establish an experimental design to prove or disprove it.

1.5.1 Background

Several studies (Valence et al., 1988; Dawson et al.,1990; Saraneva & Sääksjärvi, 2008) identified a major relationship between stress and compulsive buying. Since stress detection algorithms have been applied recently on microblogs (Lin et al., 2014; Pillai et al., 2018; Ali et al., 2018) it may be reasonable to assume that there is a relation between stressed users interacting with chatbots and their intention to make a purchase. Studies by (Seyeditabari et al., 2018) support this assumption. They found that some emotions are likely to have an influence on the decision-making process.

1.5.2 Key Variables

Status of the mind: stress will give a value One and not stress will give a value Zero.

1.5.3 Education Guess

A research study mentioned that there are relations between some emotions (stress & anxiety) and people's intention to purchase (Seyeditabari et al., 2018).

1.5.4 Null Hypothesis H_o:

There is no relation between user emotion to their online buying decision-making.

1.5.5 Alternative Hypothesis H_a:

User emotions play a significant role in online purchasing decision-making.

1.6 Methodology

This research is an experimental design using a positivist approach and data will be collected with an observation method. Collected data will be analysed with stress detection algorithms.

Availability of stress detection algorithms and the review of compulsive buyers and their intention to purchase while they are stressed bring us to hypothesize that emotion of users influence potential buyers' intention to accept a sale offer. To test the hypothesis, we will apply stress detection algorithms on a chatbot to detect users' stress. To feed our chatbot, we use script of Friends TV show which is available publicly.

Figure 1.3 shows a xml version of the chat conversation on the left and visual format for users on the right.

```xml
<?xml version="1.0" encoding="UTF-8"?>
<category>

<pattern> Hi there </category>
  <template> Hi "User's Name" and Welcome to "Campany Name" website. We are here to
assist you, in case you need any information about our Products and Services.
  </template>

<pattern>"Company Name"</pattern>
  <template> Our "Company Name" is local South African company which offer services
  such as ... and products such as ... .
  </template>

<pattern> "Product #1" </pattern>
  <template> this product is one of our best product.... </template>

<pattern> stressful </pattern>
  <template> Am sorry to hear that your day was stressful..... </template>

</category>
</xml
```

Example Responses:

User: Hi there,
Bot: Hi David, and welcome to "Company Name" Website, We are here to assist you, in case you need any information about our Products and Services.

User: I Would Like to know about your "Product #1".
Bot: this product is one of our best product...

User: I had a stressful day today and don't like to run around anymore…
Bot: Am sorry to hear that your day was stressful...

Figure 1.3 Chatbot Product Description and Stress Detection Scenario

The Diagram below (Figure 1.4) shows the process of detecting emotion and suggest the sale in a chatbot.

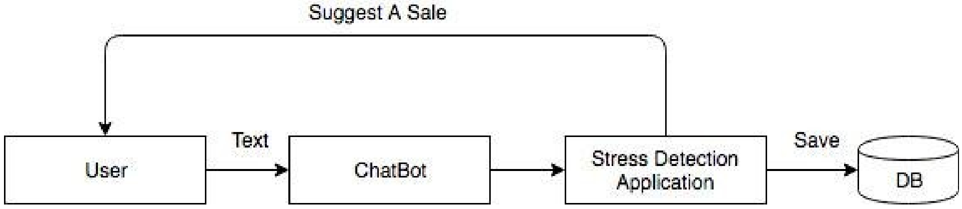


Figure 1.3 Blocked Diagram of Emotion Detection and Sale Suggestion

1.7 Contribution

1.7.1 Theoretical Contribution

This research will contribute to finding the primary emotions that have more influence on purchase decision in a chatbot. Seyeditabari et al. (2018) found that anger would have an influence on marketing and decision making. This research will extend this finding by focusing on basic emotions on a chatbot. Moreover, microblog stress detection algorithms which have been used for tweets will be modified for chatbots.

1.7.2 Practical Contribution

If the alternative hypothesis is found true, this research could enable researchers, developers, and e-commerce entities to build chatbots considering the customer emotions to reach high purchase probability. A customised chatbot application will be developed as a by-product of
this research.

1.7.3 Methodological Contribution

This study will power chatbots to not only comprehend the literal meaning of the words in a chat session with a human user (explicit information) but also understand the hidden meaning behind every sentence (implicit information) from users, and this will improve the success rate of chatbots. The implementation of the proposed conceptual framework to experiment the relationship between emotions and purchase decision making contributes to the methodological aspect of this research.

1.8 Significance of the Study

Improving chatbot performance by applying emotion detection algorithms helps software developers to produce chatbots with the capability of reciprocating in a higher level, and as a result, not only customer service companies but also small businesses could be persuaded to
add chatbots to their recaptioning systems to communicate with their clients.

1.9 Ethics

In this research, will comply with the ethical principles of the Faculty of Informatics and Design
of CPUT as well as, the general principles of experimental research such as not to manipulate
the process of data collection, and data analysis. The research will go through the ethics committee. There is no human participation involved except the researcher. The data for this research will be collected from publicly available transcripts and will be used complying fair use policy.

1.10 Organisation of the Thesis

Our research is arranged, reported, and completed in six chapters as explained below.

In the first chapter, a brief introduction outlining the context of the study is presented. The background to this study, the research problem, as well as the aims and objectives of this research, are all contained in Chapter one. Furthermore, the research hypothesis and scope of this study were also presented.

The second chapter presents background knowledge, a literature review and theories associated with this research. It started with a brief introduction to the concept, history, definition of chatbots, artificial intelligence, sentiment analysis and, analysing of compulsive buyer behaviour. Chapter 2 also presents discussions around purchase intention on e-commerce and chatbots. Chapter 2 ends with a systematic literature review showing previous relevant work and its applicability of it to this research.

Chapter 3 is a discussion on design science research as the chosen research methodology for this study. The chapter begins with a brief explanation of the research, research methodology, explaining research pyramid, including methods and techniques. According to the nature of this research, the experimental design with observation methods is selected as a research methodology for this research. Therefore, we discussed the pre-experimental, quasi-experimental, and true experimental designs and demonstrated the relevant graphs. This chapter continues by explaining our experience and motivation, as well as data collection, data analysis and limitations and potential challenges.

The fourth chapter presents a demonstration of our experimental design and goals in the first part, it expands the methodology and steps though our procedures. Then it mentions the participants who are involved in this research and their roles. Afterwards, our deviation from the initial plan and its reasonings have been explained. And lastly the conclusion of the chapter and what has been achieved in the chapter.

In chapter 5, findings gathered from background knowledge, our collected data and the systematic literature review presented in chapter 2 were used along with our experimental design presented in chapter 3 of this research. The results are demonstrated in form of four separate histograms in which purchase intention and relevant emotions are described, analysed, and compared. Moreover, in Synthesis of the Findings, we compared our findings against what we have in our literature review.

The last chapter, chapter 6 presents a summary of each chapter, then visits our aim, objectives, hypothesis which is crafted in chapter 1, our findings and accepting or rejecting our hypothesis based on the findings it continues with our recommendations, our contribution to the knowledge, self-reflection and limitations of the study which we faced during this research and at the end, we suggest potential subsequent research directing for future work.

CHAPTER TWO: Literature Review

This chapter presents and reviews subjects that form the background theory for this thesis. It provides an overview of the field of study, including a summary of the current thinking on the topic, as well as a critical evaluation of the existing research. This helps readers that are not familiar with the topics around this research to have an idea of what is necessary to comprehend the work presented in the later chapters of this thesis. The first topic presented is discussions around chatbots in Section 2.1, and then Artificial Intelligence is explored in Section 2.2. Section 2.3 represent sentimental analysis. Section 2.6 discuss Compulsive buyers. Section 2.7 discuss purchase intention in E-commerce. A systematic literature review focusing on factors that influence purchase intention on e-commerce is presented in Section 2.8. Finally, Section 2.9 summarizes this chapter.

2.1 Introduction

This chapter presents a review of the literature. The purpose of this review is to determine previous research that has been done regarding Chatbots, Sentiment Analysis, Artificial Intelligence, Compulsive Buyers, and factors that have effects on purchase intention in e-commerce as well as detecting emotions on chats, whether chatbot or tweets or TV Scripts that pertains to this research and the hypothesis. Moreover, find datasets that have been labelled by emotions (we only use datasets that have been labelled their emotions manually by individuals or tweets that have emotional hashtags by its users).

2.2 Chatbot

Chatbots are programs that mimic human conversation using Artificial Intelligence (Ranoliya et al., 2017). Cappello et al. (2017) mentioned that a chatbot is a computer program whose purpose is to imitate a conversation between humans and software to generate suitable answers from external knowledge according to the flow of the dialogue. Chatbots are not a new phenomenon, the very first chatbot was built in 1966 at an MIT AI lab and it was called Eliza. Eliza's mission was to imitate a psychotherapist. The second one was built in 1972 at Stanford University and it was called Parry. There was also, Alice, also known as Alicebot, Artificial Linguistic Internet Computer Entity, which was awarded three times in AI competitions (Khan & Das, 2017). Conversational Bots have been utilized in customer service companies recently to act as a replacement to respond to frequently asked questions on websites (Pradana et al., 2017).

Figure 2.1 demonstrates an example of a customer service chatbot correspondence with customer. It shows a simple scenario in which chatbot either able to provide the answer or not and what would be its response.

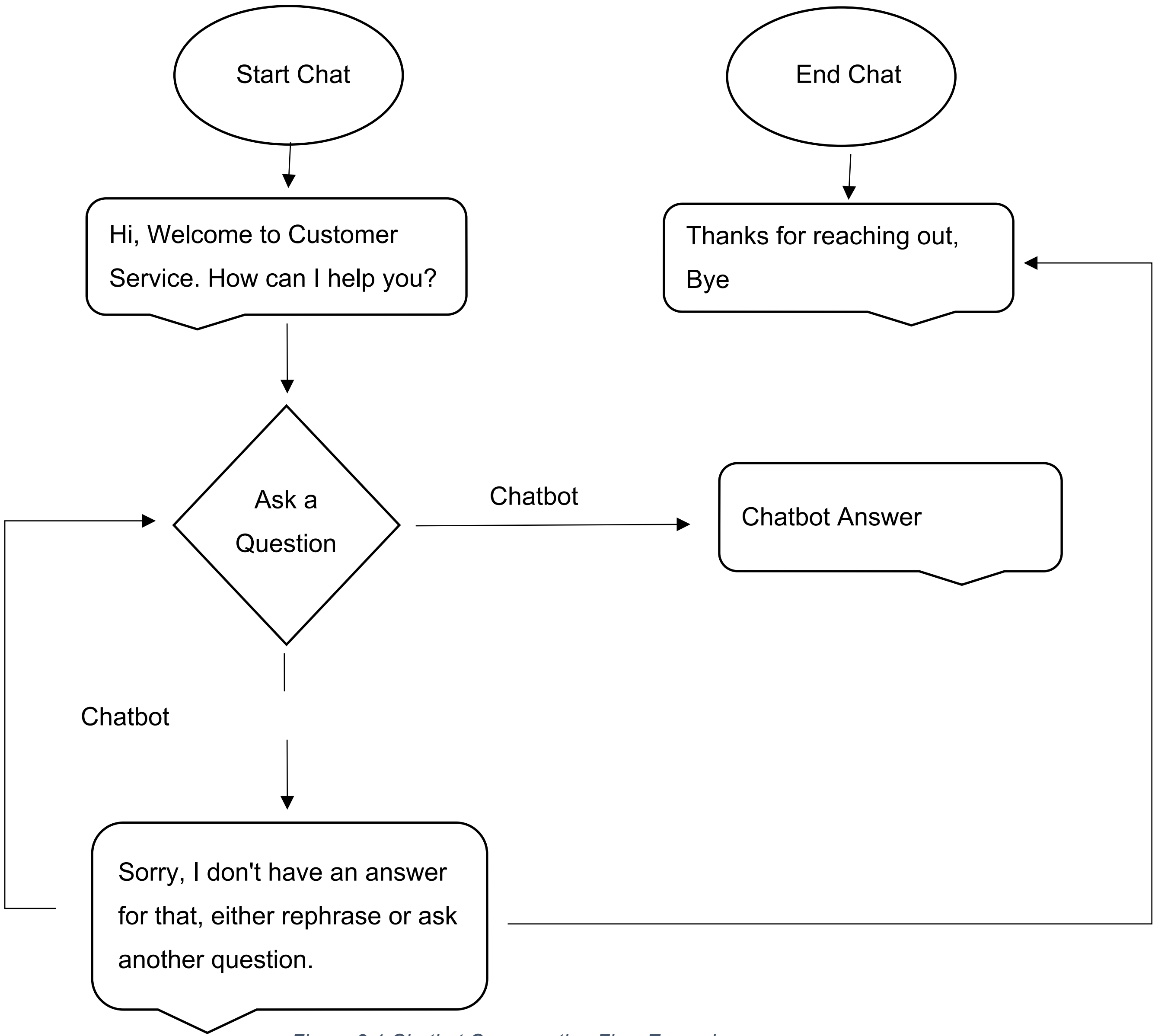


Figure 2.1 Chatbot Conversation Flow Example

The significant evolution of AI's cognitive maturity is the result of the rapid expansion of AI capabilities. This leads to 181 million interactions and 7.6 million visits by 2020, improving service efficiency, with agility, availability, accessibility, resolution, predictability, and predictability. portability. The chatbot service has reduced call centre and relationship centre queues, allowing service staff to perform more complex attendance operations (Andrade & Tumelero, 2022).

There has been a study about the impact of a chatbot on purchase intention and several factors such as perceived usefulness, ease of use, and trust have been studied, however, the result of this research could not find a factor that has a significant impact on a chatbot on purchase intention (Soares et al., 2022).

Organizations that are both internally and externally agile are able to rapidly adapt to changes in their environment and proactively respond to opportunities. This study found that chatbots can play a role in promoting agility, both through routine use in day-to-day tasks and through more innovative applications. Routine use of chatbots can help organizations become more efficient and responsive, freeing up time and resources that can be redirected to more strategic pursuits. For example, chatbots can be used to automatically answer customer questions or route inquiries to the appropriate department. This can help reduce response times and improve customer satisfaction. Innovative use of chatbots can help organizations tap into new markets and opportunities. For example, chatbots can be used to develop new customer relationships or to provide new services. By being early adopters of new technologies, organizations can gain a competitive advantage (X. Wang et al., 2022).

2.3 Artificial intelligence

Artificial intelligence (AI) and machine learning (ML) are two of the most buzzed-about topics in the tech world today. And with good reason – the potential applications of these technologies are virtually limitless. One of the most exciting potential use cases for AI and ML is in the area of data aggregation and analysis. With the ability to gather and process large amounts of data more quickly and efficiently than ever before, these technologies have the potential to revolutionize the way we make decisions. For example, imagine you're a doctor trying to diagnose a patient. In the past, you would have to rely on your own experience and knowledge to make a decision. But with AI and ML, you could have access to data from hundreds or even thousands of similar cases, which would give you a much more accurate picture of what's going on. Or imagine you're a business owner trying to decide where to open your next store. In the past, you would have to rely on your gut feeling or market research to make a decision. But with AI and ML, you could have access to data from billions of transactions, which would give you a much more accurate picture of where your customers are and what they want. The possibilities are endless. And with the rapid advancement of these technologies, we are only just beginning to scratch the surface of what they can do (Helm et al., 2020).

In recent years, there has been a growing trend of companies using artificial intelligence (AI) to help with marketing and retailing tasks. This trend is likely to continue, as AI can offer many advantages to both marketers and consumers. For marketers, AI can help to automate tasks such as customer segmentation, targeted marketing, and campaign management. This can free up time and resources that can be used for other tasks, such as developing new marketing strategies or improving customer service. AI can also help to improve the accuracy of marketing forecasts and analytics. For consumers, AI can help to personalize their shopping experience. For example, AI can recommend products that are similar to ones that the consumer has shown an interest in. AI can also help consumers to compare prices and find the best deals. In addition, AI can help to provide customer support and answer questions. Overall, AI can offer many benefits to both marketers and consumers. As technology continues to develop, AI will likely play an even more important role in marketing and retailing (M. H. Huang & Rust, 2022).

Artificial intelligence (AI) is the latest technological disruptor and holds immense marketing transformation potential. AI can help marketers automate repetitive tasks, freeing up time to focus on strategic initiatives. It can also help marketers glean insights from data to better understand customer needs and preferences. Additionally, AI can be used to personalize messages and content for individual customers, making the customer experience more relevant and engaging. AI is still in its early stages, but it is already having a major impact on marketing. For example, AI-powered chatbots are being used by brands to provide customer support and engage in conversations with customers. AI can also be used to optimize marketing campaigns, identify opportunities for cross-selling and upselling, and track customer engagement across channels. As AI continues to evolve, it will become an increasingly valuable tool for marketers, helping them to drive efficiencies, improve customer experiences, and drive growth (Verma et al., 2021).

Artificial intelligence (AI) has revolutionized the marketing industry, and chatbot marketing is one of the most exciting and innovative applications of AI technology. Chatbots are computer programs that can mimic human conversation, and they are being used by businesses of all sizes to improve customer service and support, generate leads, and close sales. AI-powered chatbots are particularly well-suited for marketing purposes because they can engage with customers in a natural, human-like way. Chatbots can be used to answer common questions, provide product recommendations, and even conduct complex conversations. With AI technology, chatbots are becoming more and more sophisticated, and they are an extremely powerful marketing tool (Cheng & Jiang, 2022).

Figure 2.2 shows a flowchart for checking the history of the customer when a potential customer is detected. It checks the previous possible orders and if it finds relevant data then it would offer a sale to the potential customer, otherwise continues the chat.

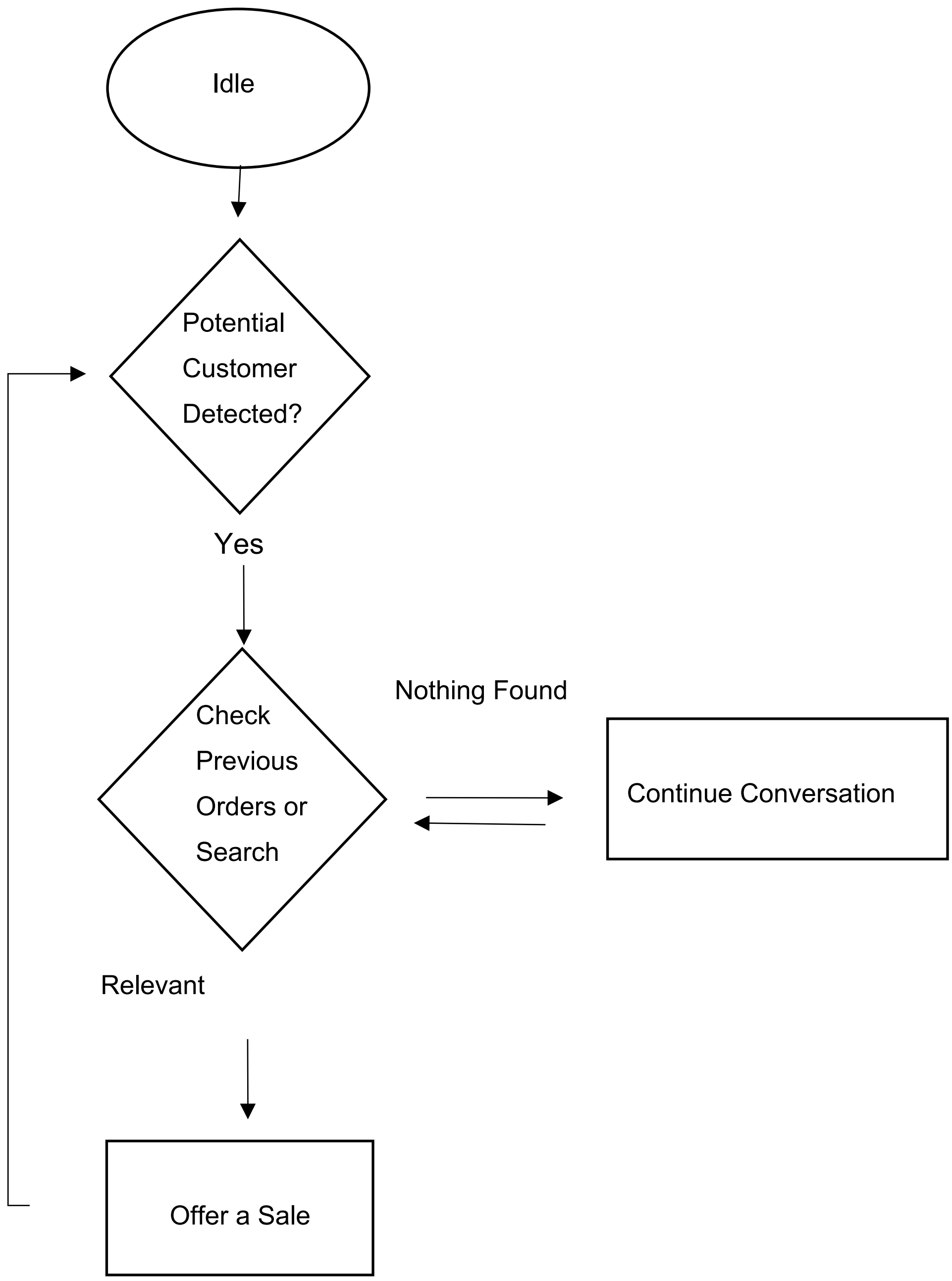


Figure 2.2 Chatbot Using Artificial Inteligence

2.4 Sentiment Analysis

As customers increasingly turn to online reviews and social media to inform their purchasing decisions, sentiment about a company's products or services has become more valuable than ever. In order to stay competitive, businesses must monitor and respond to customer sentiment to improve the customer experience. There are several ways to track customer sentiment, including social media monitoring, online review monitoring, and customer surveys. By tracking sentiment, businesses can identify areas of improvement and take steps to address customer concerns. In addition to monitoring sentiment, businesses must also be prepared to respond to negative sentiment constructively. Addressing customer concerns promptly and professionally can help to turn a negative experience into a positive one, and can ultimately help to improve customer satisfaction (S. Mukherjee, 2021).
Figure 2.3 shows how Sentimental Analysis helps to identify the Negative and Positive data. The first step is collecting the data and then Text Processing which includes Tokenization, Filtering, removing Stop Words and Stemming. Afterwards, sentimental analysis would help to detect whether the data is Negative or Positive.

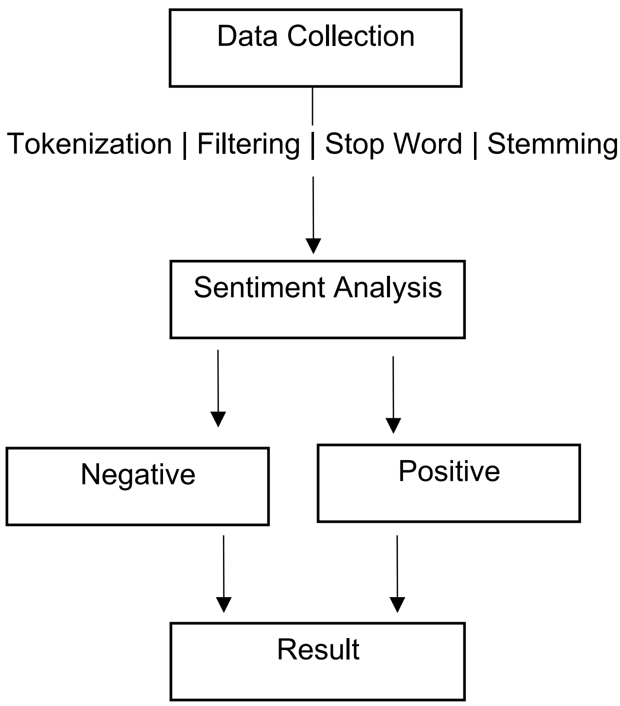


Figure 2.3 Sentiment Analysis on customer service

The analysis of customer and user reviews is always of great interest to support decision-making in many fields, especially in the field of marketing. The ability to identify and track customer and user sentiment can provide valuable insights into how well a product or service is received, what areas need improvement, and where potential new markets may exist. There are several ways to collect and analyze customer and user opinions. Social media platforms like Twitter and Facebook are increasingly being used as sources of real-time customer and user sentiment data. Online surveys and customer feedback forms are other common methods. Analyzing customer and user opinion data can be a complex task, but there are several software solutions available to help. Sentiment analysis tools can help to automatically identify and categorize opinion data, making it easier to spot trends and patterns. Overall, the analysis of customer and user opinions is a valuable tool for supporting decision-making in many fields (D'Aniello et al., 2022).

There are several reasons why retailers are increasingly using conversational AI for customer service. First, chatbots can provide a more humanlike experience than traditional customer service channels such as phone or email. This is because chatbots can simulate natural human conversation, which can make customers feel more comfortable and engaged. Second, chatbots can be available 24/7, which can be a significant advantage over traditional customer service channels that are often only available during business hours. Third, chatbots can be scaled to handle large volumes of customer inquiries, which can help to reduce operational costs. Finally, conversational AI can help to gather data about customer preferences and needs, which can be used to improve the customer experience (Tran et al., 2021).

2.5 Classification algorithms

Classification algorithms form the cornerstone of modern machine learning, representing a pivotal approach for addressing a diverse array of challenges across industries and domains. The core objective of classification is to categorize instances or data points into distinct classes or categories based on their inherent features. This predictive modelling technique underpins decision-making processes, automates categorization tasks, and uncovers intricate patterns within datasets. Among the myriad classification methods, two prominent contenders, Naïve Bayes and Logistic Regression (Setyawan et al., 2018), emerge as foundational algorithms that have withstood the test of time and application.

2.5.1 Naïve Bayes Classifier

The Naïve Bayes Algorithm is a Machine Learning algorithm. It is mainly used for text classification proposed in sentimental analysis (Krishnan et. al., 2017). The advantage of this algorithm is easiness and efficiency. The Naïve Bayes classifier, grounded in the principles of probabilistic reasoning, stands as an elegant yet formidable tool for a wide spectrum of classification tasks. This algorithm derives its strength from Bayes' theorem while introducing the "naïve" assumption of feature independence given the class label. This simplifying assumption streamlines computations and renders the algorithm amenable to a diverse range of real-world problems. Notably effective in scenarios where the dimensionality of feature spaces dwarfs the available training data, such as the classification of textual data, Naïve Bayes classifiers have etched their success in sentiment analysis, email filtering, and medical diagnosis, among numerous other applications.

Despite the algorithm's intrinsic trade-off between feature independence and real-world complexity, Naïve Bayes remains a stalwart in the classification realm. Its computational efficiency, scalability, and pragmatic performance with limited data are enduring attributes that continue to position it as a dependable tool for classification tasks in today's intricate machine-learning landscape.

Bayes Theorem is stated that the Probability of the event B given A is equal to the probability of the event A given B multiplied by the probability of A upon the probability of B.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

Equation 2.1

Bayes' Theorem for Naïve Bayes Algorithm

In machine learning classification problems, there are multiple features and classes:

$$C_1, C_2, \dots., C_K$$

Equation 2.2

The main aim of the Naïve Bayes algorithm is to calculate the conditional probability of an object with a feature vector:

$$X_1, X_2, \dots, X_n$$

Equation 2.3

Which blogs to a particular class Ci:

$$P(C_i|x_1, x_2, \ldots, x_n) = \frac{P(x_1, x_2, \ldots, x_n|C_i).P(C_i)}{P(x_1, x_2, \ldots, x_n)} \text{ for } 1 \leq i \leq k$$

Equation 2.4

2.5.2 Logistic Regression

In the spectrum of classification algorithms, Logistic Regression, often misconstrued due to its nomenclature, stands as a resolute and essential contender. Contrary to its name, Logistic Regression is at its core a binary or multiclass classifier, leveraging statistical principles to make predictions. By estimating the probability that an instance belongs to a specific class, this algorithm harnesses the logistic (or sigmoid) function to map a linear combination of features into a discernible probability score. At the intersection of statistical modelling and machine learning, Logistic Regression offers not only predictions but also interpretable insights into feature relevance for the classification outcome.

The algorithm's elegance and adaptability, coupled with its ability to capture linear relationships between features and target variables, have entrenched its prevalence in applications spanning domains such as finance, healthcare, and marketing. Although its utility thrives in cases of linear separability, researchers have embarked on diverse adaptations of Logistic Regression to address intricate classification challenges. Despite its limitations in handling nonlinear data, Logistic Regression serves as an indispensable cornerstone upon which numerous advanced classification techniques have been constructed.

2.5.3 Conclusion

In summation, classification algorithms represent the bedrock of contemporary machine learning, facilitating comprehensive comprehension of data dynamics and prediction-driven insights. Naïve Bayes and Logistic Regression, while divergent in their assumptions and foundations, emerge as indomitable pillars within the classification domain. Naïve Bayes embraces probabilistic logic and an independence presumption, flourishing in high-dimensional, language-driven contexts. On the other hand, Logistic Regression harnesses linear modelling to extrapolate class probabilities, offering not only predictions but also a window into interpretability even within intricate landscapes.

As this study delves into the intricate symbiosis between stress, chatbot services, and customer purchase intentions in e-commerce settings, Naïve Bayes and Logistic Regression shine as indispensable tools for modelling and scrutinizing customer behaviours. With their distinct characteristics, these algorithms contribute to unravelling the multifaceted dynamics of consumer decision-making in the digital era, enhancing our comprehension of the intricate fabric that weaves together human tendencies and digital interactions.

2.6 Compulsive Buyer

Valence et al. (1998) mentioned in research stress and anxiety as the main factors that stimulate spontaneous action and force buyers to diminish tensions. Moreover, there are factors such as Family Environment, Genetic Factors, Commercial Environment and Culture and advertising that dispose a person's anxiety. Faber et al. (1995) explain compulsive buyers' personalities such as low levels of self-esteem, high levels of depression, anxiety reactions and obsessions, and seeking short-term gratification from buying behaviour.

Lejoyeux & Weinstein (2010) identified three main typical behaviours of compulsive buyers which are: being repetitive, unresisting, and overwhelmed in their procurement behaviour. In addition, the tendency to purchase goods online due to the desire to avoid face-to-face social contact, the capability of concealing the purchase from relatives and the continuity of receiving online sales and offers.

The model in figure 2.4 below demonstrates the behaviour model of a compulsive buyer:

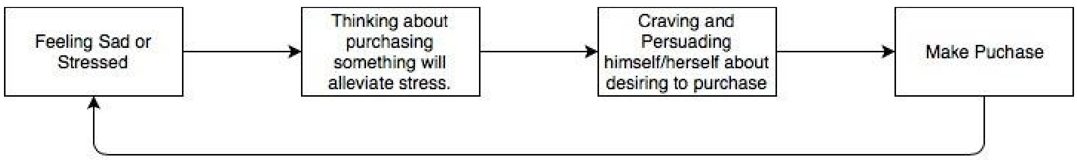


Figure 2.4 Thinking and Behaviour Model of a Compulsive Buyer

There is a growing body of evidence to suggest that smartphone addiction and online compulsive buying are related. A recent study found that people who reported higher levels of smartphone addiction were also more likely to report higher levels of online compulsive buying. Moreover, there is a strong link between mood regulatory behaviours and compulsive purchase behaviour. When people are in a negative mood, they are more likely to engage in compulsive buying to improve their mood. Flow experience is also a strong predictor of compulsive buying behaviour. Flow is a state of complete absorption in an activity, and it has been found that people who are in a flow state are more likely to engage in impulsive buying (Mason et al., 2022).

The results of the study showed that perceived stress was positively associated with online compulsive buying. Negativity has partially orchestrated this matter. This means that individuals who perceived themselves to be under more stress were more likely to engage in online compulsive buying behaviour. This is a significant finding as it suggests that stress may be a significant factor in driving this type of behaviour. Furthermore, perceived stress has a direct effect on online compulsive buying, and the mediating effect of negative coping is moderated by self-esteem. In other words, self-esteem plays a role in how people cope with stress, which in turn affects how likely they are to compulsively buy things online. This suggests that people with low self-esteem are more likely to engage in online compulsive buying when they're stressed because they're more likely to cope with stress negatively (Zheng et al., 2020). Another research suggests that problematic online purchase shopping has much in common with both offline purchasing disorders and potential specific internet use disorders (Müller et al., 2021).

The results of a recent study show that the quality of an e-commerce website has a positive influence on consumer online compulsive buying behaviour. The study found that consumers who rated the quality of an e-commerce website as high were more likely to engage in online compulsive buying behaviour (Rahman & Hossain, 2022).

2.7 Purchase Intention on E-commerce

There is a strong correlation between emotion and purchase intention in e-commerce. Consumers who feel positive emotions are more likely to make a purchase, while those who feel negative emotions are less likely to do so. This is because emotions affect our decision-making processes, and positive emotions tend to lead to more impulsive and positive decision-making while negative emotions lead to more cautious and negative decision-making (Akram et al., 2021).

There is a strong correlation between trust and purchase intention in e-commerce. Consumers who trust a particular e-commerce site are much more likely to make a purchase from that site than those who do not trust the site. This is because trust leads to confidence, and consumers who are confident in a site are more likely to make a purchase. Perceived risk is the probability that something will have a negative outcome. It can have a moderating effect on purchase intention, which is the likelihood that someone will buy a product or service. If the perceived risk is high, purchase intention is likely to be low. This is because people are less likely to take a chance on something if they think it might not work out. However, if the perceived risk is low, purchase intention is likely to be high. This is because people are more likely to take a chance on something if they think it is likely to be successful. Perceived risk is the first fear of the online shopper, even before the product or service (Qalati et al., 2021).

Perceived usefulness has a significant effect on consumer purchase intention in e-commerce. This means that the more useful a product or service is perceived to be, the more likely consumers are to purchase it. This is especially important for businesses to keep in mind when creating and marketing their products and services online. By making sure that their products and services are perceived as being useful, businesses can increase their chances of driving sales and generating revenue (Agung Ayu Puty Andrina et al., 2022; Dachyar & Banjarnahor, 2017).

While it is true that both males and females are affected by a variety of factors when it comes to choosing an online retailer, there are some key differences between the two genders. For example, studies have shown that males are more likely to be influenced by factors such as perceived website quality and convenience, while females are more likely to be influenced by factors such as security, economic reasons, and social influence.

These findings suggest that, in general, males are more concerned with the overall experience and convenience of an online retailer, while females are more concerned with factors that impact the security and affordability of their purchase. Of course, there are always exceptions to these general trends, but overall, these findings provide some insight into the key differences between the two genders when it comes to online shopping (Alfanur & Kadono, 2022).

The results of the study showed that sales volume and the number of high-quality negative comments are the most important factors influencing consumers' decision-making. This means that if a product has a lot of sales and a high number of negative comments, it is more likely to influence a consumer's decision than a product with fewer sales and fewer negative comments, while the number of comments and the number of comments with pictures are relatively minor factors influencing consumers' decision-making (Yang et al., 2022).

Previous studies suggest having prior experience interacting with chatbots doesn’t have a noticeable positive effect on product purchase intention, however, chatbots have a positive effect on users who don’t have prior familiarity with the product or brand. In contrast, chatbots don’t seem to have a positive effect on users who already have a high familiarity with the product or band (Lo Presti et al., 2021).

A study (Yun & Park, 2022) shows that trustworthiness and assertiveness positively affect customer satisfaction with and without emotional words in chatbot conversations. This means that chatbots that can provide reliable and decisive answers to customer queries are more likely to satisfy customers. Brands need to persuade customers that chatbots can perform online tasks correctly, where they work as a substitution. Moreover, This study asserts that assertiveness, which includes employees' knowledge, politeness, confidence in their abilities, and trust, should be measured as important in chatbot services. Lastly, they have emphasised the importance of empathy and correspondence with emotional words has a positive effect on customer satisfaction.

2.8 Systematic Literature Review

Systematic literature reviews are created to review, assess, and organize the literature on a topic in a systematic, explicit, comprehensive, and reproducible process. It helps to identify, clarify, evaluate, and synthesize your scope and have an unbiased review of similar conducted research while demonstrating an accurate record of research strategy. This process includes searching for relevant literature, appraising its quality, and synthesizing the findings to answer the research question. Reading similar studies can help you learn which methods have been used before (Okoli & Schabram, 2010).

There are three main stages to a successful review: planning the review, conducting the review, and reporting the review. During the planning phase, the researcher identifies the need for the review, identifies the research question, and develops a protocol for the review. When conducting a review, researchers identify and select primary studies and extract, analyze, and synthesize data. When reporting a review, researchers write reports to disseminate their findings from the literature review. This systematic literature review follows the eight steps demonstrated in figure 2.5. Step one is the formulation of the research problem, step two is the development and validation of review protocols, step three is to search for the relevant literature, step four is to screening for inclusion, step five is Quality evaluation, step six is data extraction, step seven is data analysis and integration, and sept eight is results report (Xiao & Watson, 2019).

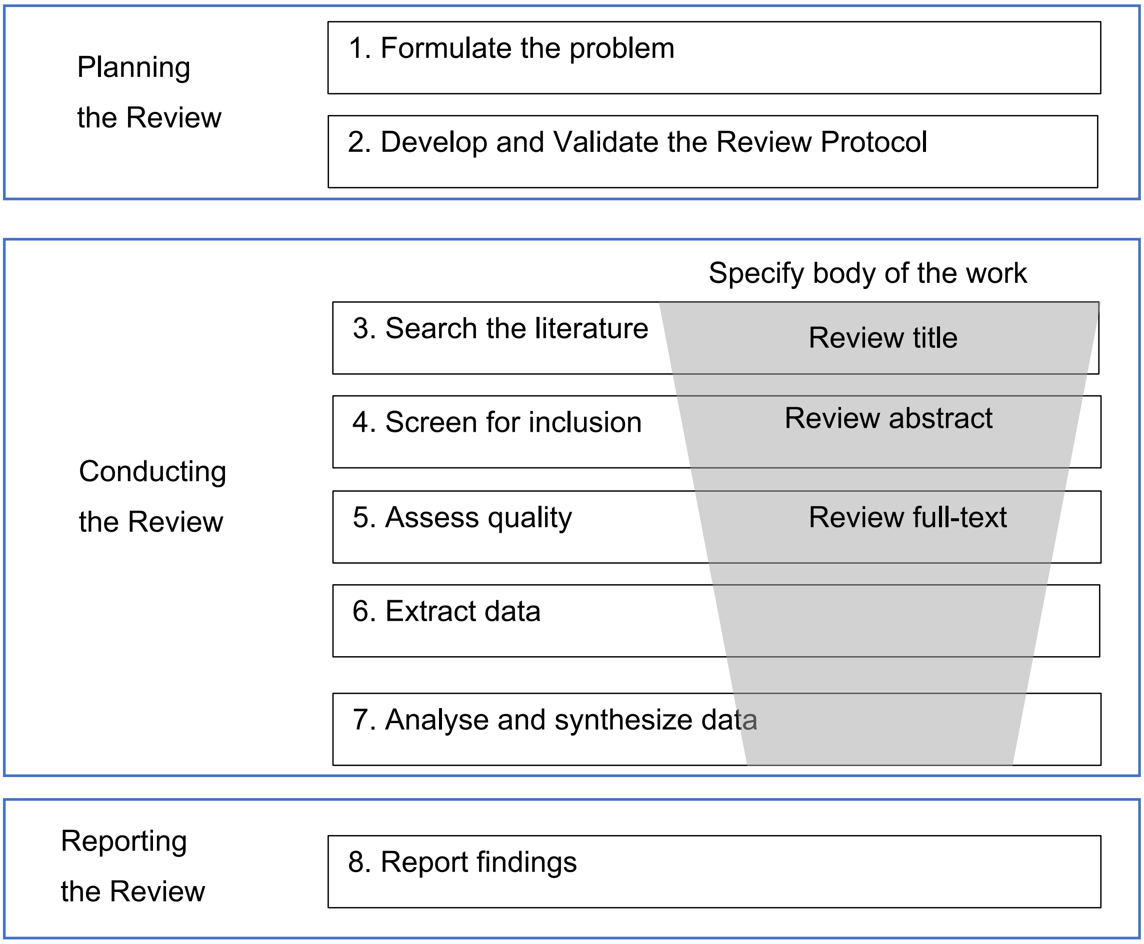


Figure 2.5 Process of systematic literature review.

2.8.1 Systematic Literature Review Questions

When conducting a systematic literature review, it is important to formulate good research questions. These questions should be specific and focused and should be based on the literature review's purpose and scope. Reviewers should also consider the type of studies that will be most useful in answering the research questions. Once the research questions have been formulated, the reviewer can then start searching for relevant studies. Framing the questions necessitates reflection, debate and reformulation. Formulating the research questions would conclude the purpose of literature review identification as the first step. Since systematic literature reviews are secondary studies that depend on primary studies they would answer only specific categories of research questions (Okoli, 2015). Since we are investigating on effects of emotions on purchase intention specifically on chatbot users on e-commerce, we need to review previous research that has worked on e-commerce and users' purchase intentions to find out whether emotions have played a big role or not. Finding out the influence of emotions on purchase intention on e-commerce can guide and lead us towards narrowing down our investigations towards chatbots as a useful tool on e-commerce to contribute to users' purchase intention.

The goal of this systematic literature review is to investigate factors that affect users' purchase intention on e-commerce and to find out whether emotions contribute to it or not. Accordingly, Table 2.1 shows the formulated review questions (RQs):

Table 2.1 Systematic Literature Review Questions

SLRQ1	What are the existing research which has identified factors that influence customers' purchase intention on e-commerce?
SLRQ2	How does each research address the factors with each other?
SLRQ3	What is the strength of evidence in support of the different solutions?
SLRQ4	What implication will these findings have on testing our hypothesis?

2.8.2 Systematic Literature Review Protocol

Establishing a protocol is fundamental to any literature review of documentation. Protocols ensure careful planning, consistency of implementation, avoiding or preventing research bias, and clarity that allows replication. To rephrase it, protocols enable researchers to anticipate problems, reduce arbitrariness, promote accountability, and maintain research integrity. The evaluation protocol included outlining the search strategy, study selection criteria, quality assessment criteria, data collection, and data synthesis. The study selection criteria include the types of studies that will be included in the review, the population of interest, the interventions of interest, the outcomes of interest, and the study design. The quality assessment criteria include the methodological quality of the studies, the risk of bias, and the applicability to the review question. The data collection includes the data that will be extracted from the studies, the data that will be collected from the authors of the studies, and the data that will be collected from the studies. The data synthesis includes the methods that will be used to synthesize the data, the results of the synthesis, and the conclusions of the review (Boell & Cecez-Kecmanovic, 2015).

2.8.3 Search Strategy

The search strategy includes the databases that will be searched, the search terms that will be used, and the inclusion and exclusion criteria for studies. Google Scholar has been used as the main search engine.

The systematic literate review has been done from the following online database shown in Table 2.2:

Table 2.2 Online Sources used in Search.

Online Research Database	URL
Google Scholar	https://scholar.google.com/
ACM Digital	https://dl.acm.org/
IEEE Explore	https://ieeexplore.ieee.org/Xplore/home.jsp
Elsevier	https://www.elsevier.com/en-xm

2.8.4 Search Terms

Post identifying the online research database, search strings should be defined that contain the most relevant keywords based on the research question and topic. Below are the search strings that have been used in the systematic literature review.

(Relationship OR Connection) AND (Emotion OR Feeling OR Sentiment) AND (Online OR Web OR E-commerce) AND (Purchase OR Buy OR Shop) AND Intention.
Table 2.3 shows the search terms in 5 categories.

Table 2.3 Search Terms

Phrase	Category 1	Category 2	Category 3	Category 4	Category 5
1	Relationship	Emotion	Online	Purchase	Intention

2	Connection	Feeling	Web	Buy	
3		Sentiment	E-commerce	Shop	
			Chatbot		

This research started based on the title, abstracts, and keywords and if the aforementioned items were considered relevant to our criteria of work, then a conclusion, finding, discussion and future work have been viewed and a summary of that work has been captured.

Category 2 contains synonyms of words with similar meanings regarding emotions. Category 3 refers to the words that have the same relevant meaning to e-commerce. Category 4 mentioned the words that are related to purchase. Category 1 conjunct Category 2 with Category 4 and 5. The category is an extra word that we thought would contribute towards finding more relevant papers as we noticed this work has been used often in e-commerce research. Combining these 5 categories generated a search string which contributed to discovering relative studies required for this systematic review. Table 2.4 shows the number of results found on each online search database along with the year.

Table 2.4 Search string execution result

Online Research Database	Number of Studies
Google Scholar	72 (2022) 48 (2021) 108 (2020)
ACM Digital	25 (2020 - 2022)
IEEE Explore	8 (2020 - 2022)
Elsevier	35 (2020 - 2022)

2.8.5 Study Selection

The selected research papers are, first, including papers that studied factors that have an effect on purchase intention on e-commerce as well as chatbots. The reason for this selection is that we had hoped to find papers that found emotions as one of the findings that influence purchase intention. The second selection was the research that specifically studies emotions as factors that could influence purchase decisions on e-commerce. The reason we covered e-commerce, as well as chatbots, was there was not enough research regarding the influence of emotion on chatbot e-commerce. Therefore, we added online shopping to the search as well.

2.8.6 Inclusion and Exclusion Policy

We narrowed down our search results using the following inclusion and exclusion criteria: Inclusion Criteria: Primary and Secondary Studies. Moreover, we did not include factors that influence Store Shopping and only covered online shopping.

Figure 2.2 indicates the abstract evaluation phase. The first step is to determine whether the title is relevant to our review and afterwards read the abstract and evaluate it.

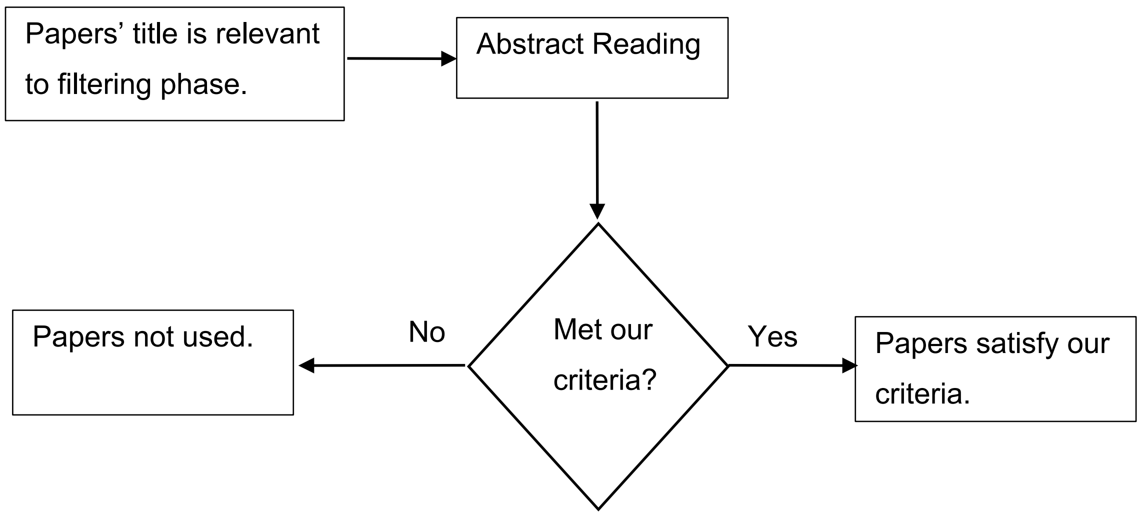


Figure 2.2 The abstract inclusion/exclusion evaluation process

2.8.7 Quality Assessment

This assessment contributes towards considering and evaluation the quality of selected papers. Previous papers suggest we follow these 5 quality assurance criteria (QAC) which are shown in Table 2.5 to evaluate our literature review: (Mohamed Shaffril et al., 2021)

Table 2.5 Quality Assessment Criteria

#	Quality Assessment Criteria
QAC1	Is the focus of the articles related to the SLR method?
QAC2	Do the papers provide all the necessary methodologies for SLR development?
QAC3	Do the articles clearly define the SLR method for the authors?
QAC4	Is there a complete explanation for each SLR method instruction in

	the articles?
QAC5	Do the articles provide an option or alternative to their recommended advice on the SLR approach?

For each criterion, we propose three options as answers which are yes, no, or partly. If the articles answer yes to four or five QACs then they are considered as high quality and if three of the QACs get yes as the answer, then the quality of the articles will be assessed as moderate quality and if two or one question gets yes it means they received a low-quality assessment. The reviewer of this study assessed,15 articles met the requirement of moderate or hight quality articles. Therefore, each answer has a scored between 0 and 1. Yes =1, Partly = 0.5, and, No =0. In the end, the sum of the scores of each response to the QACs was accumulated. If the result is greater than or equal to 2.5, the paper is accepted and used in this systematic review.

2.8.8 Data Collection

The process of data collection is critical to ensuring that the data needed to answer the research questions is collected. A data extraction spreadsheet was created with the following information:

1. Paper Title
2. Year of publication
3. Reference
4. Findings

2.8.8.1 Data Synthesis

Studies can be synthesised either quantitatively, qualitatively, or both. Quantitative synthesis of evaluation data, known as meta-analysis, is a pooling technique that focuses on the benefits and/or harms of treatment across multiple studies to provide the best estimate of effectiveness. of intervention (Mohamed Shaffril et al., 2021).

This step established procedures for organizing, analyzing, and summarizing the results of the quality assessment and data extraction phases.

2.8.9 Results

In this section, the results of the systematic literature review are presented and summarized.

2.8.9.1 Search Results

The total number of initial studies returned after the search of the selected four databases was 296 which is shown in Table 2.4. Post the initial filtering, abstract and conclusion evaluation, 281 studies were rejected. Therefore, 15 papers were selected.

Table 2.6 lists research results obtained from a carefully selected evaluation process and search terms, as well as considerations for inclusion and exclusion policies. The articles obtained answered the research questions of the literature review.

Table 2.6 Selected Study

Study	Reference	Title	Findings
S1	(Peña-García et al., 2020)	Purchase intention and purchase behavior online: A cross-cultural approach	Ease of use is a factor that evokes positive feelings of immediate appreciation and impulse buying when customers shop online.
S2	(Grigorios et al., 2022)	Overt and covert customer data collection in online personalized advertising: The role of user emotions	Personalized ads that enhance consumer emotions related to likability and confidence, such as happiness, can lead to higher product ratings and increased purchase intent. On the other hand, ads that reduce trust and familiarity, such as sadness, lower the product's rating and thus lower purchase intent.
S3	(Guo et al., 2020)	Positive emotion bias: Role of emotional content from online customer reviews in purchase decisions	Positive online reviews are comparatively more likely to purchase, demonstrating the importance of emotional bias in reviews.
S4	(Yen & Chiang, 2021)	Trust me, if you can: a study on the factors that influence consumers' purchase intention triggered by chatbots based on brain image evidence and self-reported assessments	The results showed that trustworthiness, competence, anthropomorphism, social presence, and information provision influence consumer trust in chatbots and, in turn, influence purchase intentions.
S5	(Bhatt, 2021)	Measuring Impact of Factors Influencing to Consumer Buying Intention with Respect to Online Shopping	Perceived utility, perceived trust, perceived usefulness, and perceived quality are the main components of a customer's purchase intention in an

			online shop.
S6	(M. Wang et al., 2021)	How emotional interaction affects purchase intention in social commerce: the role of perceived usefulness and product type	Improving emotional engagement and perceived usefulness can increase purchase intent.
S7	(Qalati et al., 2021)	Effects of perceived service quality, website quality, and reputation on purchase intention: The mediating and moderating roles of trust and perceived risk in online shopping	Trust has a significant impact on purchase intent in terms of website visits, increased online orders, sign-ups, website rushes, positive reviews and webstore marketing on social applications
S8	(Khoa, 2021)	The Impact of Chatbots on the Relationship between Integrated Marketing Communication and Online Purchasing Behavior in The Frontier Market	The usefulness and ease of use of chatbots are positively impacting online consumer attitudes towards a company's integrated marketing communications efforts. At the same time, integrated marketing communications lead to customer behaviors with intent to buy on impulse and repurchase.
S9	(Akram et al., 2021)	Online purchase intention in Chinese social commerce platforms: Being emotional or rational?	Hedonic motives (social shopping, adventure shopping, idea shopping, relaxation shopping) influence OPI more than utilitarian motives (convenience, choice, availability of information, lack of sociability). This suggests that online shopping in a social commerce environment has more hedonic than utilitarian motives.
S10	(Laroche et al., 2022)	An investigation into online atmospherics: The effect of animated images on emotions, cognition, and purchase intentions	showed that atmospheric online cues for video (versus static images) lead to more positive attitudes towards websites. Such effects are caused by higher levels of pleasure. This is consistent with previous studies in the context of traditional retail where atmospheric cues evoke consumer emotional states such as pleasure, which in turn influence cognitive processes and, in turn, lead to approach-avoidance responses such as higher purchases.

			consistent with the findings. intention
S11	(Lo Presti et al., 2021)	The role of the chatbot on customer purchase intention: towards digital relational sales.	Chatbots help to enhance brand awareness by decreasing the influence of familiarity on customers' purchase intention. Retailers should consider having effective chatbots when operating and designing shopping websites to drive consumer purchase intent. Businesses should carefully design and manage chatbots by monitoring user engagement and the quality of customer experience to drive continuous improvement aligned with business goals. business.
S12	(Yun & Park, 2022)	The Effects of Chatbot Service Recovery With Emotion Words on Customer Satisfaction, Repurchase Intention, and Positive Word-Of-Mouth	Findings indicate that both groups had higher customer satisfaction due to secure and reliable chatbots. Only chatbots using emotional language showed a positive impact on customer satisfaction through empathy and interactivity. Responsiveness had no effect on customer satisfaction in either group. Customer satisfaction also led to increased likelihood of repeat purchases and positive word-of-mouth for both groups.
S13	(Siripipatthanakul et al., 2021)	Factors affecting consumer's purchase intention of chatbot commerce in Thailand	According to a recent study, the anthropomorphism factor and the perceived enjoyment factor are significant predictors of purchase intention. This means that if a product is perceived as being enjoyable to use and/or having humanlike qualities, people are more likely to want to buy it. However social interests don't have the same impact
S15	(Jiang et al., 2022)	Chatbots in retail: How do they affect the continued use and purchase intentions of Chinese consumers?	First, the social presence of chatbots has a direct and positive impact on retailer innovation and intimacy. Second, the retailer's experience-based sense of innovation, intimacy, and empowerment mediates the impact of chatbot social presence on

			consumer behavioral intentions. Third, great communication styles in low-level social beings are very helpful in fostering the relationship between social beings and experiential innovation. Can play an important role in fostering relationships.

2.8.9.2 Quality Evaluation

The selected studies were assessed for quality using the demonstrated questions in section 2.8.7. Table 2.7 is a summary of the results of the quality assessment phase. This table displays the selected papers that are qualified and their quality assessment score from 5.

Table 2.7 Quality evaluation of selected studies

Study	AQC1	AQC2	AQC3	AQC4	AQC5	Total
S1	1	0.5	1	1	0	3.5
S2	1	0.5	1	1	1	4.5
S3	1	1	1	1	0.5	4.5
S4	1	0.5	1	1	1	4.5
S5	1	0.5	1	1	0.5	4
S6	1	1	1	1	1	5
S7	1	1	1	1	0	4.5
S8	1	0.5	1	1	0	3.5
S9	1	1	1	1	1	5
S10	1	0.5	1	1	1	4.5
S11	1	0.5	1	1	0	3.5
S12	1	0.5	1	1	1	4.5
S13	1	1	1	1	1	5
S14	1	1	1	1	0.5	4.5
S15	1	1	1	1	1	5

2.8.10 Analysis

This section presents an analysis of the result from the systematic literature review based on our four research questions in Section 2.8.1

2.8.10.1 SLRQ1: What are the existing research which have identified factors that influence customers’ purchase intention on e-commerce?

There are several types of research which identified factors that influence purchase intention in e-commerce. Some of these factors include product attributes, perceived risks, perceived benefits, perceived value, and customer satisfaction.

2.8.10.2 SLRQ2: How does each research address the factors with each other?

The literature covers different factors such as positive feelings, happiness, and confidence during shopping, positive reviews that have been posted for the product from other users, or trustworthiness of the online shop as well as ease of use.

Product attributes refer to the features of the product that are attractive to the customer. Perceived risks refer to the customer's perceived risks in making a purchase, such as the risk of not receiving the product or not being satisfied with the product. Perceived benefits refer to the customer's perceived benefits of making a purchase, such as the convenience of online shopping or the ability to find good deals. Perceived value refers to the customer's perceived value of the product, such as the quality of the product or the price. Customer satisfaction refers to the customer's satisfaction with the purchase process, such as the ease of use of the website or the speed of delivery.

Each of these factors can influence the customer's purchase intention. For example, if the customer perceives a high risk in making a purchase, they may be less likely to do so. Or, if the customer perceives a high value in the product, they may be more likely to make a purchase. Satisfied customers are also more likely to make repeat purchases. Thus, it is important for e-commerce businesses to understand these factors and how they can influence purchase intention.

2.8.10.3 SLRQ3: What is the strength of evidence in support of the different solutions?

The literature has shown their findings based on the data they have provided from online shops and questionaries.

2.8.10.4 SLRQ4: What implication will these findings have on testing our hypothesis?

Previous research mentioned emotion or feeling as one of the factors that influence e-commerce however, they have not specified which state of emotion has more impact on the intention to purchase.

2.8.11 Systematic Literature Review Summary

A thorough search and study of factors that influence customers' purchase intention on e-commerce were presented in the systemic literature review.

The review identified 15 studies that were working on purchase intention behaviour on e-commerce and different factors impacting the purchase or persuading the customers or making them come back again to visit the website and make them more involved with the e-commerce. Furthermore, the impact of positive emotions, trust, and quality of the website on e-commerce. Moreover, factors of chatbot customer service in purchase intention and retail.

2.8.12 Systematic Literature Review Limitation

The chatbot product was built in 1966 and there has been major development of the chatbots specifically in the past decade, however, studies related to detecting emotions from chatbots have not been developed as much as other aspects of the chatbot such as the informational part. We could not find previous research related to the effect of emotions or stress on chatbots and e-commerce. Therefore, we framed our systematic literature review toward a closer topic to our research topic which we thought finding on it would contribute towards our study.

There are previous papers that have studied factors that influence purchase intention in e-commerce and the role of chatbot customer service in e-commerce. However, studying the type of emotion or explicit emotions and their impact on e-commerce is not specifically mentioned in the previous research.

2.9 Chapter Summary

This chapter reports on a systematic literature review that was conducted. The review was based on published literature related to the aim of this research (1.4).

The literature shows there have been interests in finding out factors that influence customers to purchase e-commerce and they have found that emotion and positive feelings about the website or product have an impact on purchase intention among many other factors, focusing specifically on emotions and the type of emotions that has an impact on purchase is missing from the literature. There is research that focuses on the factors that influence purchase intention in e-commerce. Moreover, they found that happiness can lead to higher product ratings and as a result leads to more purchases and sadness causes lower product ratings and therefore less purchase intention in e-commerce.

CHAPTER THREE: Methodology

A brief description of our chosen methodology has been mentioned in Section 1.6 of the first chapter. This chapter discusses the methodology and research process that is used in this experimental research.

The purpose of research methodology is to provide a structure and framework for conducting research. It helps to ensure that research is conducted systematically and ethically and that findings are robust and credible. Research methodology also allows researchers to be replicable and repeatable.

Section 3.1 shows an introduction to the research methodology. section 3.2 demonstrates the Research Pyramid, Section 3.3 reports the experimental design. Section 3.4 mentions the research strategy. Data collection is noted in section 3.5. experiences and motivation are mentioned in section 3.6. our data analysis has been described in section 3.7. Our limitations and potential challenges have been mentioned in Chapter 3.8. Lastly, the summary of this chapter is mentioned in section 3.9.

3.1 Introduction

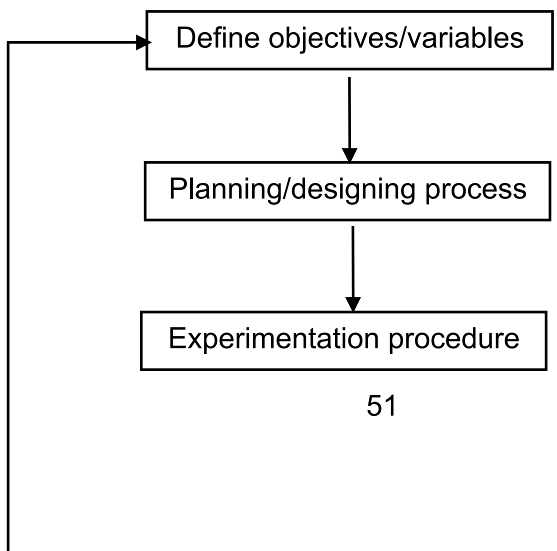
The purpose of research is to gain knowledge and understanding about a particular topic or issue. It involves collecting and analyzing data and then using that information to conclude. Research can be used to improve our understanding of the world around us, and to make better decisions about how to improve our lives. it is an important tool that helps us to understand the world around us. It allows us to find out new information and test our hypotheses (S. P. Mukherjee, 2020).

There is no single definition of research methodology. It is a broad term that can refer to a wide range of activities and approaches, all of which are used in the pursuit of knowledge. The methodology can include everything from the design of experiments to the collection and analysis of data and the interpretation of results. It is important to remember that no single methodology is the "right" one and that the best approach for any given project will depend on the nature of the question being addressed. Research methodology is the process used to collect data and information to conduct research. It includes the methods and techniques used in research, as well as the tools and resources used to collect data and information (Mishra & Alok, 2017).

Experimental design is the process of conducting research in an objective and controlled manner that amplifies accuracy and allows specific conclusions to be drawn concerning hypothesis statements. In general, the goal is to determine the effect of a factor or independent variable on the dependent variable. A true experimental design is one in which the relationships between and among variables are tested. In general, one variable, the independent variable, is controlled to study the effects of other variables, the dependent variables. True experiments are important in research because they allow for cause-and-effect conclusions to be drawn.

Several features are characteristic of true experimental designs. First, there is a control group, which is not exposed to the independent variable, and an experimental group, which is exposed to the independent variable. Second, there is a random assignment to the groups, so that each participant has an equal chance of being in either group. Third, the groups should be similar to each other in all relevant respects except for the independent variable. Finally, the effects of the independent variable are measured by comparing the experimental group to the control group.

Figure 3.1 illustrates the comprehensive workflow for experiment planning, execution, and analysis, encompassing various stages from defining objectives to drawing conclusions. The process is organized into six sequential steps, each of which plays a pivotal role in ensuring a systematic and robust experimental approach.



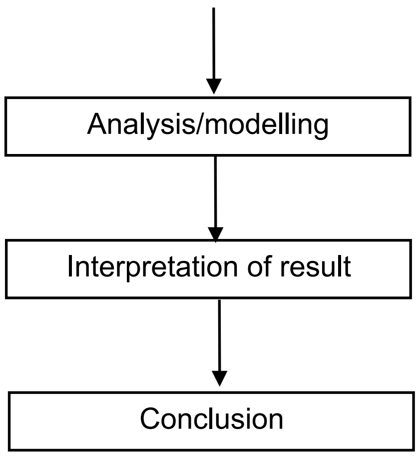


Figure 3.1 Experiment Planning

True experimental designs are the most rigorous type of research design, and as such, they are the most likely to yield valid results. However, they can be difficult and expensive to implement, and so sometimes other designs, such as quasi-experimental designs, are used instead (Bell, 2009).

Positivist designs are meant for theory testing and seek generalized patterns based on an objective view of reality. In positivist research, the researcher is typically concerned with testing hypotheses and verifying or disproving theories. Positivist designs are based on the assumption that there is an objective reality that can be studied and that the researcher can remain objective and unbiased in their observations. This type of design is often used in the physical and natural sciences.

This study employs an experimental framework grounded in the positivist paradigm. Data will be acquired through an observational methodology, and subsequently subjected to analysis via stress detection algorithms. The presence of established stress detection algorithms, coupled with an examination of compulsive buyers and their purchasing inclinations under stressful conditions, prompts the formulation of a hypothesis suggesting a causal relationship between user emotions and the propensity of prospective buyers to embrace sales offers. To empirically investigate this hypothesis, stress detection algorithms will be implemented within a chatbot environment to discern user stress levels. The input data for the chatbot will be sourced from the publicly accessible script of the television show "Friends."

3.2 Research Pyramid

The research pyramid (Jonker & Pennink, 2010) is a tool that can be used to help researchers plan and organize their research projects. The pyramid is divided into four sections, each of which represents a different stage of the research process. The four sections are Research Paradigm, Research Methodology, Research Methods, and Research techniques. The research paradigm is the way that the researcher sees and specifies the primary approach. Research methodology is the approach to doing the research which is related to the research paradigm. The research methods show the particular phase to practice which required to be done in a specific order. And the research techniques using tools used for data collection and analysis. Figure 3.2 This figure illustrates the hierarchical structure of a comprehensive research inquiry, depicted as a pyramid comprising four integral components: Research Techniques, Research Methods, Research Methodology, and Research Paradigm.

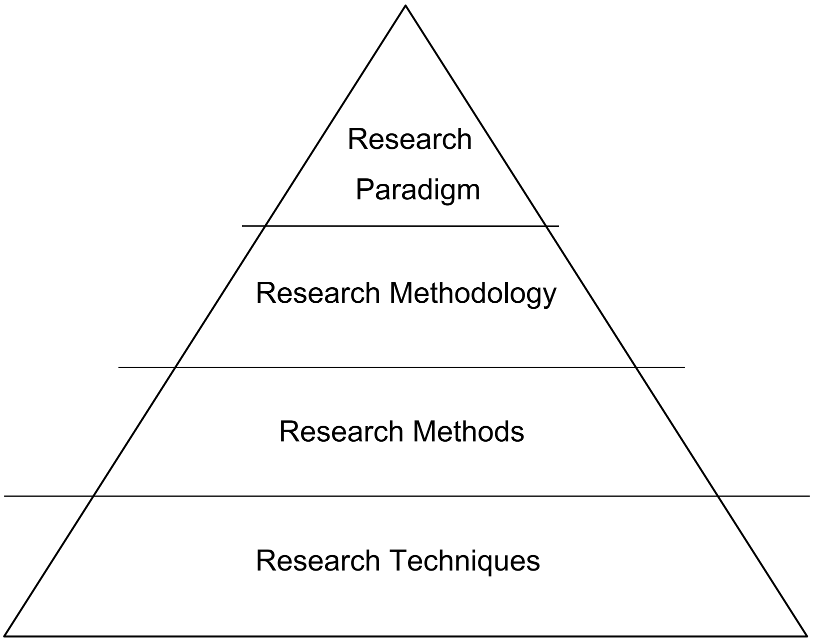


Figure 3.2 Research Pyramid Hierarchical Components of Research Inquiry

3.2.1 Research Paradigm

A research paradigm is a set of assumptions and beliefs that guide a researcher in their work. It is a framework that helps to shape the research process and the output of the research. Many different research paradigms can be used, and the choice of paradigm will often depend on the type of research being undertaken. The main paradigms are positivist, interpretivist, and critical. Positivist research is based on the idea that there is an objective reality that can be studied and measured. Interpretive research, on the other hand, focuses on the meanings and interpretations that people give to their experiences. Critical research takes a more transformative approach, seeking to challenge and change existing structures and power relations. There is no single correct research paradigm, and different researchers will often adopt different paradigms depending on their own beliefs and values. However, it is important to be aware of the different paradigms and how they can shape the research process (Jonker & Pennink, 2010). Positivism conforms to the hypothetical-inferential model of science based on the verification of a priori and experimental hypotheses by operating variables and measures; The results of hypothesis testing are used to inform and advance science. Studies involving positivism typically focus on identifying explanatory or causal relationships through quantitative approaches, where empirical findings from sample sizes In this respect, generalizable inferences, replicating results, and controlled experimentation are the guiding principles of positive science (Park et al., 2020).

3.2.2 Research Methodology

Research methodology portrays the global course of actions involved in the research process without specifying individual actions. In this way, the methodology serves as a guideline for the research process. A methodology is a system of methods and principles for conducting research. It is a way of approaching a research problem, and it includes the theoretical framework within which the research will be conducted. A methodology presents the primary route towards a goal, however, doesn't indicate every single step. It serves and defines sets of principles and global directions. The methods, on the other hand, are the specific tools and procedures that will be used to collect and analyze data. Methods cover techniques in detail which depends on the research hypothesis and questions. The choice of methodology and methods will be based on the nature of the research problem and the objectives of the research (Jonker & Pennink, 2010).

3.2.2 Research Methods

Research methods refer to the behaviour and instruments used in selecting and constructing research techniques (Kothari, 2004). Research methods refer to particular steps that need to be taken in definite order during the research.

3.2.2 Research Techniques

Research techniques refer to the actions and tools used in conducting research activities, such as observation, data recording, and data processing techniques. Many different research techniques can be used to collect data and information. Some common research techniques include surveys, interviews, focus groups, and observations. Observations are another common research technique that can be used to collect data. Observations can be either structured or unstructured. Structured observations involve observing people in a controlled setting, while unstructured observations involve observing people in their natural environment (Kothari, 2004).

3.2.3 Conceptual Framework

A conceptual framework is a conjunction of relevant concepts that supply meaning and concepts' relations together.

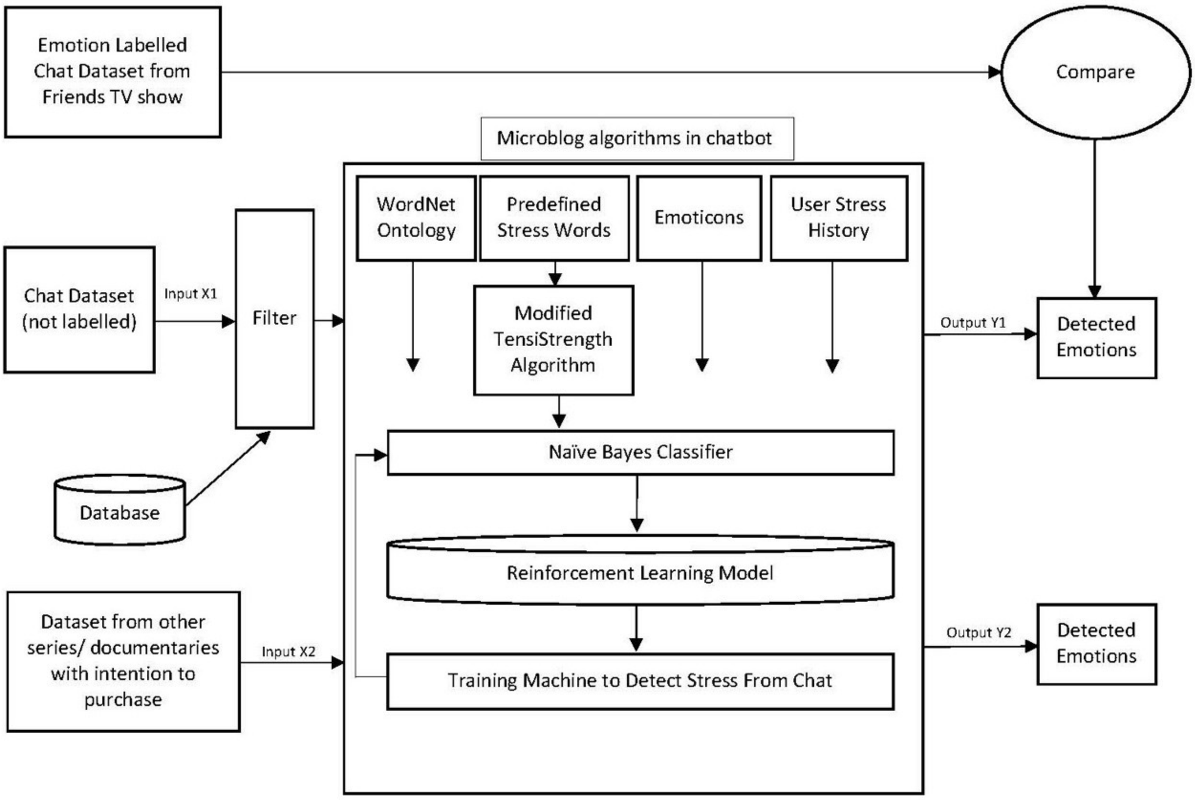


Figure 3.3 Conceptual Framework

In this model, Figure 3.3, we use microblog algorithms, emotion detection and classifiers. First, the process of detecting emotions from the Friends' TV Show dataset and finding out the accuracy of detected emotions from the unlabelled emotion chat dataset with the emotion-labelled chat. And then use other publicly available datasets (other TV shows and documentaries about shopaholics) to find out whether there is a relation between emotions and the probability of making a purchase.

3.3 Report the Experimental Design

A quantitative study is based on a rigorous and systematic approach to data collection, analysis, valid instrument, and appropriate research design. This type of study is often used to test hypotheses or to examine relationships between variables. Quantitative studies are typically conducted using statistical methods, which can provide a great deal of detail and accuracy.

The goal of experimental design is to ensure that the data collected during the experiment can be used to answer the research question, as well as produce meaningful and defensible evidence. This means that the design must be appropriate for the type of data that will be collected and the questions that will be asked. The design must also be able to control for any variables that could potentially influence the results (Brown & Melamed, 2012).

3.3.1 Probability

Probability is a central concept in experimental design. It is used to quantify the chances of various outcomes occurring and to determine the most likely outcome of a given situation. Probability can be used to determine the best course of action to take in a given situation and can be a valuable tool in decision-making (Brown & Melamed, 2012).

3.3.2 Dependent and independent variables

In experimental design, the dependent variable is the variable being measured or observed, while the independent variable is the variable being manipulated or controlled. In other words, the dependent variable is the outcome of the experiment, while the independent variable is the variable that is being changed.

Experimental design is all about finding cause-and-effect relationships. In order to do this, the independent variable must be varied while everything else is kept constant. This allows the researcher to see how the change in the independent variable affects the dependent variable.

For example, in a study investigating the effect of studying on test performance, the independent variable would be the amount of time spent studying, while the dependent variable would be the score on the test. By varying the amount of time spent studying, the researcher can see how this affects test performance.

3.3.3 Population

In experimental design, the population term is used to refer to the entire group of individuals or objects that are being studied. This group is usually defined by certain characteristics, such as age, gender, race, or geographic location. The population can also be divided into subgroups, which are then used as the units of analysis in the study.

In this experiment, we have 4 groups of datasets which have been labelled with emotions.

3.3.4 Pre-experimental Designs

Pre-experimental designs are research designs that do not involve the manipulation of independent variables. These designs are typically used to generate hypotheses or to explore relationships between variables. Pre-experimental designs are usually less rigorous than experimental designs, and as such, they are less likely to produce valid and reliable results.

3.3.4.1 One-Shot Experimental Case Study

A one-shot experimental case study is a type of research design that is used to examine a single case. This type of study is often used in situations where it is not possible to randomly assign subjects to different conditions. One-shot experimental case studies are sometimes criticized for being too limited in scope, but they can be useful for generating hypotheses and exploring new ideas. Figure 3.4 shows the One-Shot Experimental Case in which Group represent the group that we are conducting a study on. Tx represents the treatment on the dependent variable. Obs represents our observation.

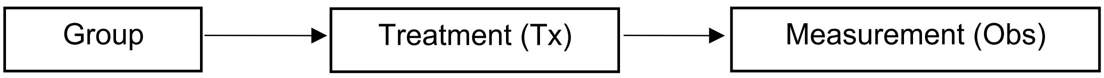
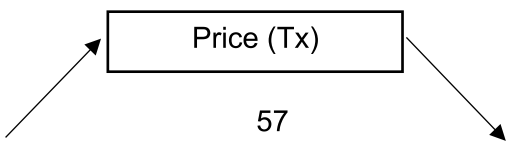


Figure 3.4 One-Shot Experimental Case

The reason we chose this experiment is that there might be many reasons for a user to make a purchase online and we don't know all the factors that influenced the user to buy a good or service. For example, a customer made a purchase, and we checked his/her emotional state and we found out it was Joy. Therefore, we formulate our experiment as having Joyfulness would cause the customer to place an order. However, we are only considering the user's basic emotional estate as the dependent variable and didn't consider other variables such as the product price or usefulness or a combination of them with positive emotions which we are demonstrating in figure 3.5 below:



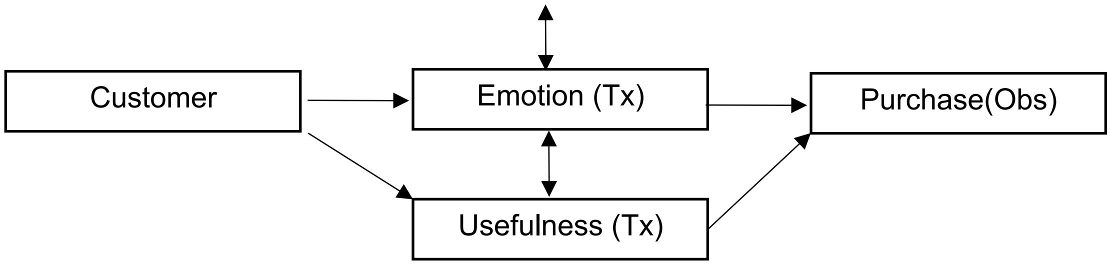


Figure 3.5 Possible dependent variables

Pre-experimental designs are modest to implement however the results may not be reflective of what is being measured because of the absence of a comparison group. Moreover, we won't be able to conclude a generalization based on our experiment due to not being able to manipulate or randomize the independent variable and having unknown variables in our study.

3.3.5 Quasi-experimental design

A quasi-experimental design is a type of experimental design that uses observational data to answer research questions and casual hypotheses (White & Sabarwal, 2014). Quasi-experimental designs are often used when it is not possible or ethical to randomly assign participants to treatment and control groups or its impractical. Quasi-experimental designs can be used to study both cause-and-effect relationships and associations. In a cause-and-effect relationship, the independent variable is the cause, and the dependent variable is the effect. In an association, both variables are associated with each other, but there is no causal relationship.

Without randomization, there is no guarantee that the two groups will be similar in any respect before the experimental intervention or treatment and there is no guarantee that they are completely different. However, an initial observation (e.g., a pre-test) can confirm that the two groups are at least similar in terms of the dependent variable under study.

In our research, we have four groups of datasets. Each group of datasets has been extracted from previous researchers who made their datasets publicly available. These groups are different from the source of being generated, the EmotionLine is a dataset from TV Series, CARER is a dataset from Twitter, GoEmotions is a dataset from Reddit comments and EmotionPush is a dataset from Facebook Messenger. Moreover, these datasets are not similar in having the same amount of data. However, there are similarities and relevance that make them suitable for our study which is all four datasets contain short sentences, all have been labelled by basic emotions, all contain words that show intention to purchase, and all are corresponding chats.

3.3.5.1 Posttest-only Control-Group Design

The ideal experimental design for our research would be having one or more controlled groups of customers and we offer them a sale and record their accept or deny answer while we are observing their emotional state for our research. Regrettably, we don't have such datasets. Thus, we are unable to pretest our dataset. The only option we have in true experimental design, due to our limitations, is to observe whether the purchase happened in a Neutral or Non-neutral emotional state. Therefore, we compare these neutral and non-neutral emotional stats. Non-neutral emotions vary in each dataset, however, there are some similarities such as Joy and Sadness.

The Limitation of this study is in purchases which have been labelled Neutral. All four datasets which we use in our research have been conducted from previous research. In this research individuals who labelled each sentence by the relevant emotions, have been instructed that they have to choose neutral emotions when they cannot comprehend the sentence emotion 100 per cent or there are mixed emotions and there are no predominant emotions or there are no emotions involved. Therefore, having a sentence labelled as neutral does not necessarily mean the sentence is neutral, it means the emotional state of the sentence could not be determined. Moreover, we were targeting the datasets that have similarities with chats in a chatbot, these datasets all contain short sentences and in many of these short sentences, there is not enough context to indicate the purchase. This means there might be some purchases that have emotions in the overall look of the entire chat session, but this could not be determined as emotions on each sentence have been conducted.

In our experimental design, we did not pick up our datasets and purchase records in a random way and used the entire dataset.

3.3.6 True Experimental design

A true experimental design is one in which the researcher has full control over the independent and dependent variables. This type of design is used when the researcher wants to be able to draw causal conclusions from the data. To do this, the researcher must manipulate the independent variable and measure the effect on the dependent variable.

True experimental designs are considered to be the most rigorous and are therefore the most powerful type of design.
Due to our limitation mentioned on Quasi-experimental Design regarding our datasets, we are unable to run a true experimental design on this research.

3.3.5 Experimental Validity

Experimental validity is the process of determining whether or not a scientific experiment is reliable and accurately measures what it is supposed to measure. Without experimental validity, an experiment is essentially worthless. There are three main types of experimental validity: internal validity, external validity, and construct validity. Internal validity is the validity of the results of an experiment within the experiment itself. External validity is the validity of the results of an experiment when applied to the real world. Construct validity is the validity of the measurements used in an experiment.

3.3.5 Random Sampling

Random sampling is used to select a sample of individuals from a population. The sample size is typically small, and the individuals are chosen using a random process.
There are several factors to consider when determining an appropriate sample size for a study. The first is the type of study being conducted. For example, an exploratory study will require a smaller sample size than a confirmatory study. The second factor is the population being studied. A larger, more diverse population will require a larger sample size to be representative. The third factor is the desired level of precision. Studies with a higher level of precision will require a larger sample size to achieve this. Finally, the cost and feasibility of conducting the study must be considered. Larger studies will require more resources and may not be feasible for some research projects. In conclusion, many factors must be considered when determining an appropriate sample size for a study. The type of study, the population being studied, the desired level of precision, and cost and feasibility must all be taken into account (Lakens, 2022).

In this research, we are unable to use random sampling due to the nature of the data that we collected which are from four different previous research.

3.3 Research Strategy

We have found four datasets that have been labelled by basic emotions and are publicly available to use. These datasets consist of four different types of chats. The first one is

EmotionLines (Chen et al., 2019) which has the entire utterances from the Friends TV series. The second one is CARER(Saravia et al., 2018) which is English Tweets. The third one is GoEmotions (Demszky et al., 2020) which is from Reddit comments and the fourth one is EmotionPush (C. Y. Huang & Ku, 2018) which is from Facebook messenger.
Since we want to check the purchase intention on these datasets, first we filter the chats that indicate purchase intention by relevant keywords, such as buy or purchase and their synonyms, such as deal, acquire, and take.

Then we do our observation process by checking the identified emotion for each sentence that had the purchase intention and create a histogram according to it separately.

Lastly, test our hypothesis based on the generated result and histogram and accept or reject the hypothesis accordingly.

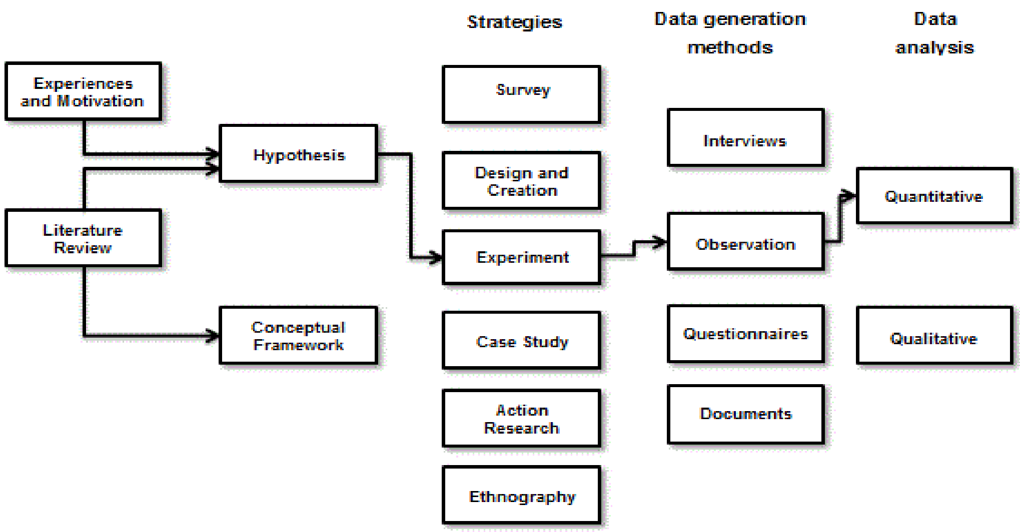


Figure 3.6 Model of the Research Process (Oates 2005)

The research strategy employed in the experimental study is depicted in Figure 3.6 above. The amalgamation of experience, motivation, and a comprehensive literature review culminated in the formation of the research hypothesis and the corresponding conceptual framework. The methodology employed was designed to assess the validity of our hypothesis. The experimental setup, in turn, was guided by the conceptual framework.

3.4. Data Collection

Our first objective in chapter 1 (section 1.4.1) is to research and acquire datasets to test our hypothesis (section 1.5). These datasets must have two key specifications. The first is to be in the form of a corresponding chat generated from a chat history or a series of comments or tweets generated from the history of social media websites. Second, these datasets must have been labelled by related emotions, such as joy, sadness, anger etc. Moreover, the detected emotions on these datasets should be produced by humans and not another machine or software to be able to trust the detected emotions. During our literature review process, we found four datasets that have the above specifications as demonstrated in Table 3.1 below: EmotionLines (Chen et al., 2019), CARER (Saravia et al., 2018), GoEmotions (Demszky et al., 2020), EmotionPush (C. Y. Huang & Ku, 2018)

Table 3.8Collected Datasets Description

#	Dataset	Brief Description
1	EmotionLines	Dialogues extracted from the Friends TV Series are labelled by Basic emotion: Anger, Disgust, Fear, Happiness, Sadness, and Surprise. The dialogue emotions were identified by humans in a survey.
2	CARER	Tweets extracted from the tweeter. They are in English Language and their emotions were identified by their authors' given hashtags. Emotions are Anger Anticipation, Disgust, Fear, Joy, Sadness, Surprise, and Trust.
3	GoEmotions	The datasets are extracted from Reddit comments based on 27 emotions.
4	EmotionPush	Messages are extracted from Facebook Messenger with 7 emotions: Joy, Anticipation, neutral, tired, anger, fear, and sadness

3.4. Experiences and motivations

The motivation for this research was to determine customers' emotions while they interact with chatbot customer services and find the best user’s emotional state to offer a sale. Currently, chatbots focus more on improving the quality of interaction with customers by understanding the request and delivering the most relevant answer in a more informative way. Comprehending emotion from chat would help chatbot clients to correspond with the chatbots naturally and hence help to be persuaded more to interact with a chatbot over humans. Moreover, this would make users trust to associate with chatbot more often and feel confident about their requests and concerns being understood.

Another motivation for this research is to collect databases that are created by other researchers and are available publicly which are in short text corresponding formats such as TV scrips, Facebook Chats, Tweets from Twitter or comments on websites like Reddit and are labelled by relevant emotions manually by users through a questionnaire or other form of projects. These valuable databases will help to develop, train and test chatbot algorithms that require the chat's emotions to be identified.

This research could also give more insight into the gap in previous research about the influence of emotional factors such as Joy, Fear, Sadness, anger, etc. on users' purchase intention on chatbots and generally e-commerce websites.

3.5 Data Analysis

A hypothesis is a proposed explanation for a phenomenon. A scientific hypothesis must be testable and based on observable evidence. The scientific method involves observing the phenomenon, formulating a hypothesis, testing the hypothesis, and then either accepting or rejecting the hypothesis based on the results of the experiment (Kothari, 2004).

To test our hypothesis and analyze the data, we are going to extract the sentences in the chat which are referring or indicate any intention to purchase by observation method and then capture that sentence's emotional estate. We searched through the entire dataset and extracted all sentences and didn't create a sample size because the number of sentences on each dataset that referred to purchase is not overwhelming, therefore we used all the extracted data to have more accurate results. Lastly, we use a chi-squared test to finalize our hypothesis test to accept or reject the alternative hypothesis. A chi-squared test is a statistical test used to determine whether two or more groups are significantly different from each other. The chi-squared test is used to compare observed data with expected data. The chi-squared test is used to determine whether there is a significant difference between the expected frequencies and the observed frequencies in one or more categories.

3.5.1 Null hypothesis and alternative hypothesis

The alternative hypothesis is often the one we hope to prove and the null hypothesis is the one we hope to disprove. The null hypothesis is symbolized with H0 and the alternative hypothesis is symbolized with Ha.

Null Hypothesis H0: There is no relation between user emotion to their online buying decision-making.
Alternative Hypothesis Ha: User emotions play a significant role in online purchasing decision-making.

3.5.2 The level of significance

It is an imperative part of testing our hypothesis. The suggested percentage is 5 per cent (Kothari, 2004). this means when choosing a significance level at 5 per cent, then H0 will be rejected when observed evidence has less than 0.05 probability of occurring if H0 is true. it means we take a 5 per cent risk of rejecting the null hypothesis when H0 happens to be true.

3.5.3 Decision rule or test of hypothesis

The decision rule refers to the number of items we test before accepting or rejecting the hypothesis as well as the number of defective items in our sample. However, we do not take a sample and take all the items in four datasets and check the number of purchase intentional sentences.

3.5.4 Type I and Type II errors

Testing a hypothesis always has a chance of mistakes and rejecting a hypothesis when should have been accepted (type I) or accepting the hypothesis when should have been rejected (type II). We fix the type I error on 5 per cent which means there is a 5 per cent chance of rejecting the hypothesis when it is true.

3.6. Limitations and Potential Challenges

We tried to use only datasets that are emotionally identified by humans, however, there are still some limitations regarding choosing the right emotion per sentence. Many chats either have mixed emotions or neutral emotions, in this case, emotion identifiers are instructed to check the neutral as the emotion. Another limitation was having access to a real customer service chat history which has been identified by relevant emotions or an e-commerce website with a chatbot or chat with agent dataset with the relevant emotions.

3.7 Summary

In this chapter, we showed the research process which was aligned with utilizing the research pyramid containing the Research Paradigm, Research Methodology, Research methods and Research Techniques and our conceptual framework. Then we described the Design Science Research (DSR), DSR framework, DSR process and its six steps. Afterwards demonstrate our research strategy, data collection and data analysis.

CHAPTER FOUR: Experiment Planning and Setup

4.2 Experimental Goals

An experimental design goal is to ensure that the experimental design is valid and reliable. This means that the design must be able to produce accurate and consistent results. Many factors can affect the validity and reliability of an experimental design, so it is important to carefully consider all of these factors when planning the experiment. The goal of an experimental design is to create a design that is as close to perfect as possible so that the results of the experiment are as accurate and reliable as possible. The goal is to supply an absolute conclusion of relationships of variables in the research hypothesis based on our Education Guess.

The goal of this experimental research is to find out whether there is a relation between users' emotions and their purchasing decision-making process.

4.3 Procedure

The first step is to find out datasets that are labelled with associated emotions. During our literature review process, we found four datasets that have labelled emotions and these emotions are being assigned to the chat either by the chats' author-like hashtags or by the individuals who were instructed to read the chats and choose from their given basic emotions. All these datasets should have similarities with chatbot conversations.

The second step is to review these datasets with an observation method and filter the chats, sentences or utterances that show any intention to make a purchase or buy a good or service. The purchase intention chats are our independent variables and the emotions associated with them are our dependant variables.

The third step is to demonstrate and compare the extracted data from step two in the form of a table, chart, and histograms and test our hypothesis to accept or reject it.

4.1 Introduction

This chapter discusses the experimental goals and setup as well as how the experiment was carried out. Moreover, we discuss our datasets and how we utilized the collected datasets in our research. We also discuss the tasks and procedures that were performed to conduct the research. It involves deviations from the plan as well.

4.3.1 EmotionLines

EmotionLines (Chen et al., 2019) have generated an emotion dialogue dataset from Friends TV Scripts and labelled each utterance. The list of basic emotions in this dataset is Anger, Disgust, Fear, Happiness, Sadness, and Surprise. Figure 4.1 below shows the dataset structure which Speaker, Autterance, Emotion and Annotation. In this research, we focus on Utterance and Emotion.

The dataset is available through this link:
http://doraemon.iis.sinica.edu.tw/emotionlines/download.html


```
    },
    {
        "speaker": "Rachel",
        "utterance": "Anyway uh, great idea!",
        "emotion": "joy",
        "annotation": "1400000"
    },
    {
        "speaker": "Rachel",
        "utterance": "Umm, I gotta go to the store; I told him that I would buy him some more tissues.",
        "emotion": "neutral",
        "annotation": "5000000"
    },
    {
        "speaker": "Monica",
        "utterance": "Oh, we have some",
        "emotion": "neutral",
        "annotation": "5000000"
    },
    {
        "speaker": "Rachel",
        "utterance": "No you don\u0092t!",
        "emotion": "non-neutral",
        "annotation": "0010211"
    }
],
```


Figure 4.4 EmotionLines Sample Data which is labelled by the detected emotion.

4.3.2 CARER

CARER (Saravia et al., 2018) generated a dataset from English tweets from Twitter based on hashtags. The list of emotions in this dataset are Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise, and Trust. Figure 4.2 shows a few sentences from the dataset. It starts with the sentence and ends with the relevant emotion as a hashtag.

```
3. i really want to go buy some yardage of art gallery just to play
   with because it feels so amazing;#surprise
4. i get into what it actually does i feel like everyone should buy
   it just because it smells amazing;#joy
5. i just feel so discontent about my life these days;#sadness
6. im starting to not buy the whole everything happens for a reason
   bit or god has a plan b c i feel that god is love and theres no
   way that he would torture me and other women like weve been
   tortured dealing w fertility issues;#anger
7. i feel like i have reached a plateau where im not buying as much
   as i use to and feeling more satisfied with my wardrobe and
   personal style;#joy
```

Figure 4.5 Example of CArer tweets with their emotional Hashtags

4.3.3 GoEmotions

GoEmotions (Demszky et al., 2020) built their dataset manually which contains 58K Reddit comments labelled based on 27 emotions plus Neutral. Figure 4.3 below show the excel format of the the GoEmotions dataset along few example that contains id, text and the relevant emotion that has the number 1 on columns.

1	id	text	anger	annoyance	approval	disappointı	disapprova	disgust	embarrassı	excitement	fear	joy
2	ef8i9z6	Not necessarily. Poor people tend to purchase cheaper foods, and have assistance programs that	0	0	0	0	0	0	0	0	0	0
3	ed5v2bf	I donâ€™t think his clothing was so tight when he purchased it..	0	0	0	0	0	0	0	0	0	0
4	ee4kvyp	Sneaky ass ESPN changing their app so I almost accidentally purchase ESPN+ for the low price of 4	0	0	0	0	0	0	0	0	0	0
5	eewo54a	I'm sure the cleaning bill he caused isn't even remotely offset by the flights he's purchased.	0	1	0	0	0	0	0	0	0	0
6	ef7dvml	Including the fact that once I pirate something, i usually will purchase it later on either through fru	0	1	0	0	0	0	0	0	0	1
7	ee8gmy3	Also since so many are forgoing children or having fewer the is less needed to purchase very large	0	0	0	0	1	0	0	0	0	0
8	edph179	If she stole a wallet with an activated card, or something along those lines. Once it's purchased, it'	0	0	0	0	0	0	0	0	0	0
9	ee8gmy3	Also since so many are forgoing children or having fewer the is less needed to purchase very large	0	0	1	0	0	0	0	0	0	0
10	edfnmek	I do take Vitamin C, daily. I purchased some probiotics yesterday. Hope those will help.	0	0	0	0	0	0	0	0	0	0
11	ef7dvml	Including the fact that once I pirate something, i usually will purchase it later on either through fru	0	0	0	0	0	0	0	0	0	0
12	ef7dvml	Including the fact that once I pirate something, i usually will purchase it later on either through fru	0	0	0	0	0	0	0	0	0	0
13	eelgfhz	What if I dont want the service? Why should I be forced to purchase that service?	0	0	0	0	0	0	0	0	0	0
14	edpiohy	Bitch real man just panicking purchases a m82 barret..Now excuse me while i hide from my wife f	0	0	0	0	0	0	0	0	1	0
15	ef7dvml	Including the fact that once I pirate something, i usually will purchase it later on either through fru	0	0	0	0	0	0	0	0	0	0
16	edph179	If she stole a wallet with an activated card, or something along those lines. Once it's purchased, it'	0	0	0	0	0	0	0	0	0	0
17	ee4kvyp	Sneaky ass ESPN changing their app so I almost accidentally purchase ESPN+ for the low price of 4	0	0	0	1	0	0	0	0	0	0
18	eelgfhz	What if I dont want the service? Why should I be forced to purchase that service?	0	0	0	0	0	0	0	0	0	0
19	edph179	If she stole a wallet with an activated card, or something along those lines. Once it's purchased, it'	0	0	0	0	0	0	0	0	0	0
20	ee4kvyp	Sneaky ass ESPN changing their app so I almost accidentally purchase ESPN+ for the low price of 4	0	1	0	0	0	0	0	0	0	0

Figure 4.6 GoEmotions Sample Data

4.3.4 EmotionPush

EmotionPush (C. Y. Huang & Ku, 2018) labelled 8,826 messages from Facebook Messenger manually with 7 emotions: joy, anticipation, neutral, tired, anger, fear, and sadness. Figure 4.4 shows the sample of datasets which includes speaker, utterance, emotion and annotation.


```
    {
        "speaker": "2235381",
        "utterance": "but I did tell my boss that we shoudl buy yesterday",
        "emotion": "neutral",
        "annotation": "5000000"
    },
    {
        "speaker": "2235381",
        "utterance": "but then TVIX dropped in the afternoon after being flat at 2%",
        "emotion": "neutral",
        "annotation": "4010000"
    },
    {
        "speaker": "2255151",
        "utterance": "Oh well",
        "emotion": "neutral",
        "annotation": "3020000"
    },
```


Figure 4.7 EmotionPush Chat Example

4.4 Participants

The experiment had no participants other than the researcher. The researcher was the only person involved in this study. In this regard, permission or ethical considerations are not required before conducting research.

The participant interacted with the websites on the internet and looked for the datasets which suites this research. The literature review component provided insight regarding the previous research about e-commerce and chatbots and factors that influence purchase intention. Our systematic literature review also showed the gaps in the previous research papers about relations between emotions and purchase intention in e-commerce and specifically chatbots.

4.4 Deviation from the plan

There is always a risk of deviating from the set-out plan in any experiment or set up. This is because no matter how well the plan is designed, there is always the potential for human error. This could be something as simple as a mistake in the measurements or a misunderstanding of the instructions. Even if the experiment is carried out exactly as planned, there is always the possibility that the results could be different from what was expected.

In our research, we could not run a true experimental design due to the differences between our four datasets in dependent and independent variables. Although our dependent variables in each dataset have some similarities in emotions such as Joy and Sadness, however, there are differences between these emotions as well and there are some emotions that are not common in all the datasets such as Power. Our independent variables also have some similarities such as they are all coming from short sentences, chats, TV dialogues, or tweets, however, these four datasets are not generated from similar sources so there are differences as well. Thus, we only could run a Quasi-experimental design.

Another deviation was about the purchase intention in a chatbot. We could not find any previous research about studying the purchase intention in chatbots in customer service companies, therefore, we focused on factors which have an impact on purchase intention in e-commerce and the impact of customer service chatbots on e-commerce because of the similarities we thought they have together. For example, we thought there might be a similarity between factors that influence users to purchase from e-commerce and chatbot or if chatbot persuades customers to interact with the e-commerce more, this might lead to purchasing.

Moreover, lack of previous research that specifically focused on the impact of stress in chatbots, therefore, we focused on the general term of emotions to find out if there are specific emotions that have an impact on purchase intention or not. We hoped our findings could help to find some relations between stress and emotions. For example, nervousness, sadness, or anxiety are related to stress.

4.5 Conclusion

In chapter four, we expanded on the methodology discussed in chapter three. Chapter four explained more in detail about experimental design and goals. Moreover, we walked through the steps we took in this chapter. We noted the participants who are involved in this research and their roles. And lastly, we mentioned the deviation from the initial plan and their reasonings.

CHAPTER FIVE: Findings

The main goal of this research has been presented in chapter 1 which is to discover chatbot users who have the intention to purchase a good or service while they are corresponding with a bot.

The first section of this chapter is summarizing the research objectives. Section 5.2 presents the description and analysis of our results for each of the objectives plus viewing the datasets from Neutral and Emotional states. Section 5.3 shows our hypothesis testing on each dataset. Section 5.4 contains a synthesis of the findings and section 5.4 contains a summary of this research.

5.1 Introduction

This research focuses on measuring the effects of emotions on user purchase intention on chatbots. This would power chatbots with a feature that can help have a profound understating of users' conversations with chatbots. This would have benefits for both chatbot users and companies that utilize chatbots on their e-commerce websites as assistants or customer service companies to handle customers' enquiries. Chatbot users would have the benefit of having a chat with a bot which have multiple channels of understanding the user in both an informative and emotional way. This would persuade chatbot users to chat more with the chatbot and get the accurate information they require. It would benefit E-commerce websites and customer service companies from a financial perspective. An E-commerce website would have a better understanding of users' emotional states to offer them a sale in the most efficient time. Customer service companies would reduce operational costs by utilizing these chatbots and handling complicated chats with a human agent only.

Based on our research aim, a hypothesis was introduced in chapter 1 (section 1.5) which says emotions play an important role in chatbot users' purchase intention. to test our hypothesis three objectives have been developed (section 1.4). The first objective was to discover datasets which are labelled by emotions. These datasets should be in the form of corresponding chats, like Facebook messenger or tweets, due to their similarity with chats and being in short sentence formats or other formats of dialogues like TV shows or comments. The second objective was to identify sentences, tweets or comments which show an intention to purchase. The third objective was to find out each sentence's emotions and report the result as histograms to accept or reject our hypothesis.

Moreover, a systematic literature review was done in this research to find out the existing research that worked on factors that have an impact on customer purchase intention on e-commerce and chatbots. The result of the systematic literature review indicated that there are some relations between website users' emotions and feelings with purchase intention on e-commerce such as trusting the online shop, enjoyment of the process, and the overall look and feel of the website, however, there were a few research, limited to our research criteria mentioned in section 2.8 as SLR protocols, to show what emotion has an impact on purchase.

5.2 Description and Analysis of results

We suggested a hypothesis (section 1.5) and defined three objectives to test our hypothesis to accept or reject it. In the next three subsections, we show in detail how we addressed each objective and how we completed them.

5.2.1 Objective 1: Find datasets that have been labelled by emotions

To accomplish our first objective of this research and be able to test our hypothesis we are required to have datasets that are labelled by emotions. These datasets must be in the form of chats or have similarities with chats. There are many datasets in the form of long sentences that have been labelled by emotions however this doesn’t suit our purpose. The big challenge in detecting emotions on short chats which often happens on chatbots is there are few words on the chat and detecting the correct emotions on the chat is extremely difficult. Therefore, working on datasets which have emotionally labelled and have long paragraphs wouldn’t suites our research. Moreover, we could not find any datasets that have been the actual record of a chatbot with customers that have been labelled by emotions. Another important specification that these short chats must contain is that emotions should be labelled by humans and not machines. The reason for that is to make sure the detected emotions are labelled correctly. Therefore, the closest datasets that we could find were either Facebook chats, because of having the same nature of the short chats, tweets, because of having limited characters on the tweets which give the similarity to chatbot conversation, TV series utterances, which give the correspondence in chat similarity as well has to have short sentences and comments on other social media which give again the same similarity of short sentences and some occasional corresponding. We hoped the datasets that have similarities with chatbot conversations help us to test our hypothesis, however, ideally, we would need actual chat history from customer service companies which needed to be labelled by humans and not machines to make sure detected emotions are correct.

5.2.2 Objective 2: Identify the sentences or utterances that have mentioned buy/purchase or show intention to purchase;

Our four datasets are in the format of plain text format (.txt), JavaScript Object Notation (.json), and Comma-separated Value (.csv) formats. A sample of each dataset is demonstrated in Chapter 4 (section 4.3). Identifying chats that show purchase intention has happened by observation methods. We search words that indicate purchase on those files. The main words that we searched were 'Buy' and 'Purchase' in our first round of searching. However, to refine and make sure we are not missing other words that indicate purchase, we searched for synonyms of purchase words such as obtain, acquire, take, deal and gain. We were facing two challenges here. The first one was finding the words with multiple meanings such as 'buy'. Although this word was the first purchase indicator word that we searched for, however, this word can also have the meaning of disagreement or not being convinced in sentences. For example, if the chat has the sentence 'I don't buy it', this could also have the meaning or 'I disagree' or 'I don't believe it'. Therefore, we had to read the few sentences above and below that specific chat to make sure the meaning of the word was there. The second challenge was the words that are very usable in many formats in the English language like 'Take'. Take has many meanings and only one of many is to agree to buy something. Therefore, we are again required to read more of the sentence below and above the page to find out the correct answer.

Nevertheless, we could identify the chats which have purchase intentions.

5.2.3 Objective 3: Check the emotion that is associated with that sentence and create histograms based on that result.

We generated histograms based on the result we could achieve on our second objective.
In each section below we indicated the total number of sentences which we could get out of each dataset and then showed the number of sentences which indicate purchase intention. then checking the emotion associated with the sentence and creating histograms

accordingly. Our four histograms indicated in which emotional state each sentence had shown any intention to purchase a good or service.

In the below sections, we demonstrate the histograms for each dataset separately.

5.2.3.1 EmotionLines

In the EmotionLine dataset, we have over 10800 chat dialogues. About 19 of them showed intention to purchase. Out of those 19 sentences Neutral and Joyful emotion played the biggest role, Joyful with 8, Neutral with 6, Mad with 4 and Powerful with 1 purchase intention. Many sentences were identified and other emotions which means it was not clear what is the precise emotion associated with the sentence, however, this did not have an effect or result as this number was zero. The emotion line indicates that Neutral, Joy and Surprise appear more often in the datasets this is regardless of purchase intention in the sentence (Chen et al., 2019). Figure 5.1 below shows the EmotionLines purchase intention histogram.

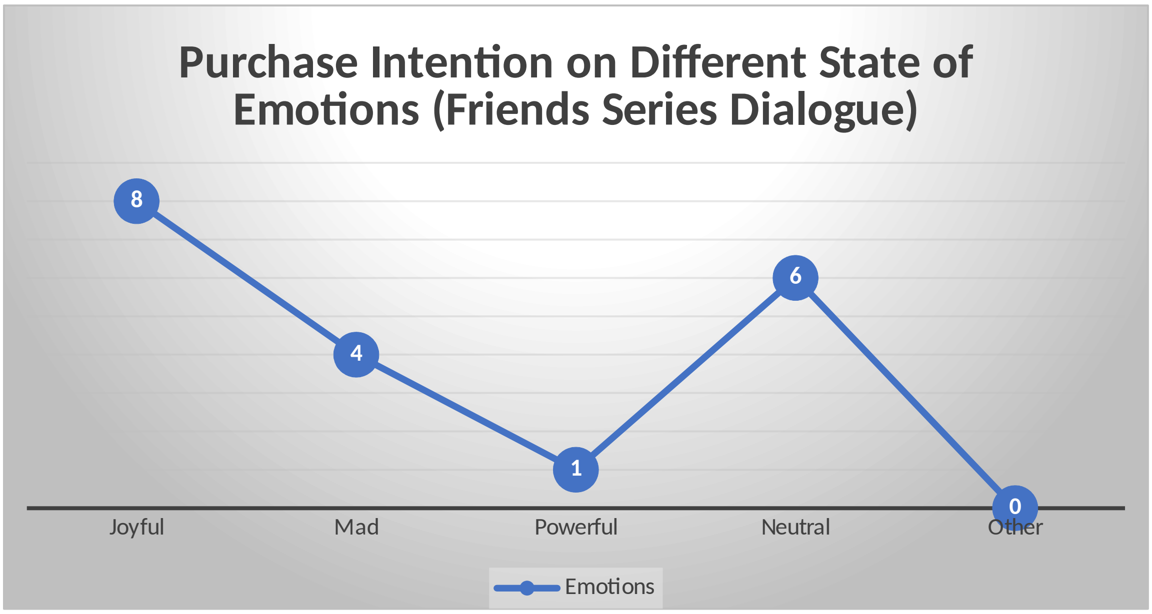


Figure 5.8 EmotionLines Histogram

5.2.3.2 CARER

The CARER dataset contains over 11300 tweets which have been labelled with relevant emotions with hashtags via their authors. Our analysis indicates that 66 sentences have demonstrated intention to make a deal and out of these 66 tweets there is Joy plays the biggest role with 32 purchase intentions and its number is doubled by the second emotion Sadness with 15 intentions to buy. Fear is the third one with 10 intentions, anger has 7, Surprise has only 2 and same as Emotionline, tweets with unknown emotions have been labelled as others which again is zero here. Figure 5.2 shows the CARER purchase intention histogram.

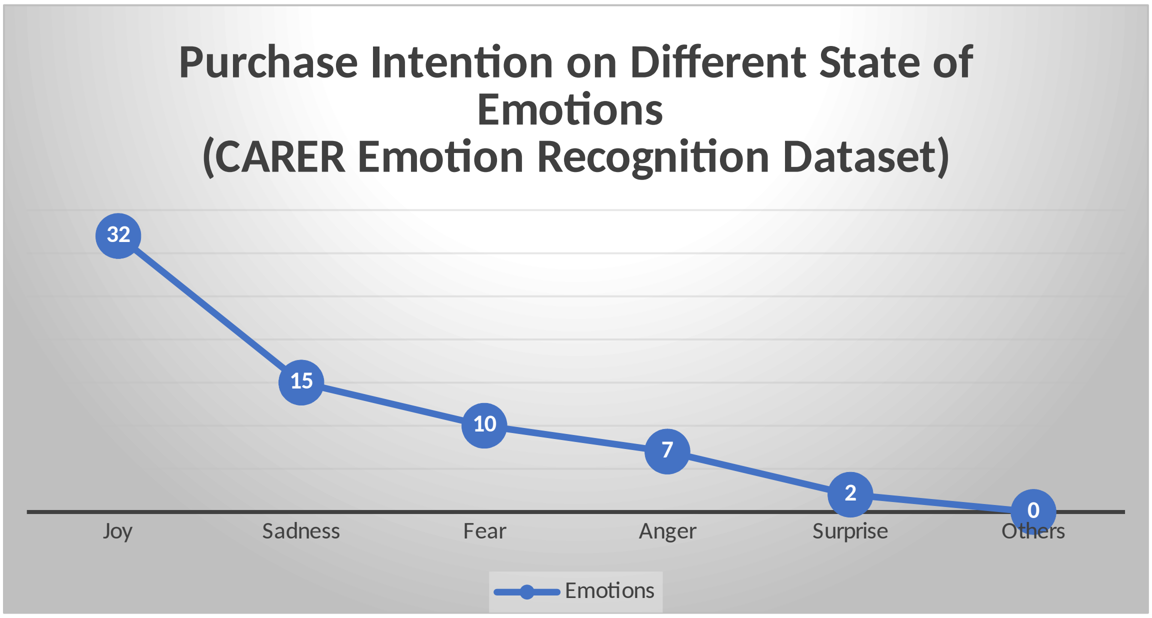


Figure 5.9 CARER Histogram

5.2.3.3 GoEmotion

GoEmotion has over 211200 comments from Reddit. 318 of these comments showed an intention to acquire goods or services. Neutral played the biggest emotion in this dataset with 251 intentions to buy. Joy and Anger have close results to each other, Joy is 24 and Anger is 21. Then Sadness has the number 13 intention and Fear and Nervousness have the number 5 and 4 purchase intention as the record. Figure 5.3 shows the GoEmotion purchase intention histogram.

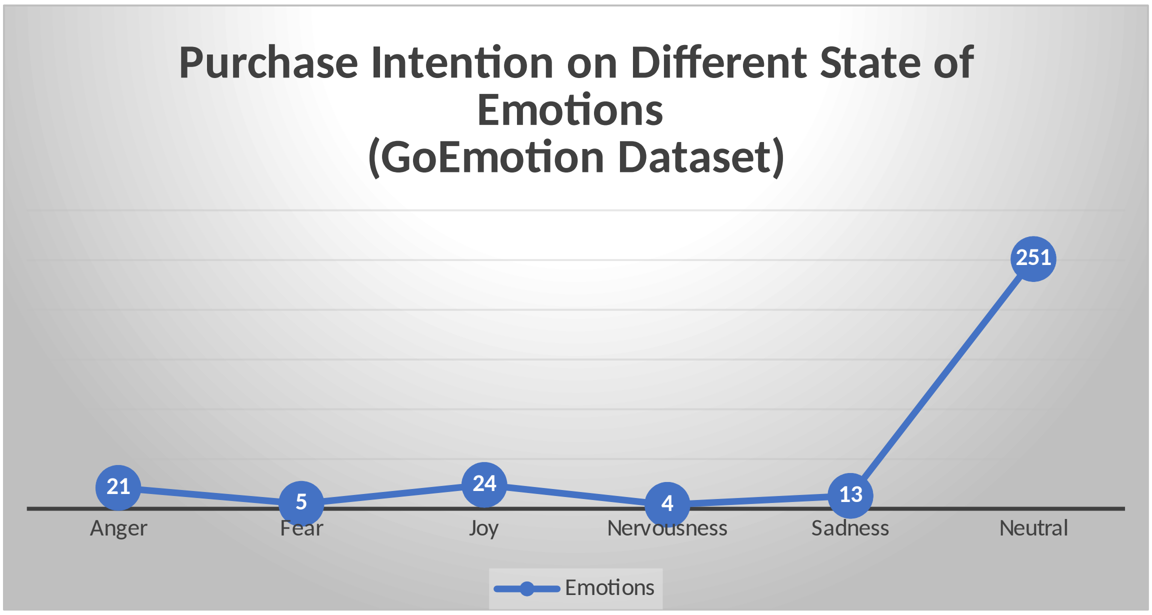


Figure 5.10 GoEmotion Histogram

5.2.3.4 EmotionPush

Emotion Push includes over 10900 Facebook messages. out of this number, 34 messages show intention to get a good or service. Neutral has the biggest number of 31 and Joy by far is the second with 3 intentions. The other emotions like Anticipation, Tired, Anger, Fear and Sadness have zero purchase intention. Figure 5.4 shows the EmotionPush purchase intention histogram.

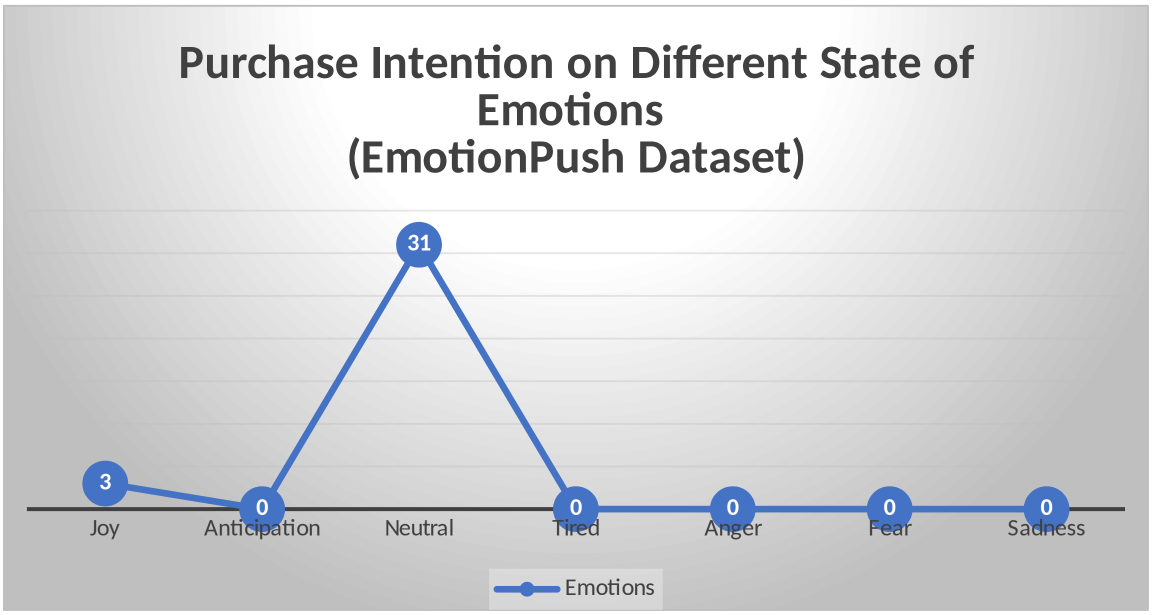


Figure 5.11 EmotionPush Histogram

5.3 Users' Neutral and Emotional state comparison on Purchase Intention

In Section 3.3.5.1 we discussed our posttest-only control group design and its limitations. Table 5.1 below demonstrates the table of four datasets in detail of neutral and nonneutral purchases.

Table 5.9 Neutral and Non-neutral Purchase in our Four Datasets

Datasets	Purchased	Neutral Emotion	Non-neutral Emotion
EmotionLines	Yes	6	13
CARER	Yes	0	66
GoEmotions	Yes	251	67
EmotionPush	Yes	31	3

Figure 5.5 below demonstrates the comparison of users' neutral and emotional states in our four datasets. In EmotionLine, six purchase happened while users' emotion was neutral and thirteen purchase occurred while users' emotion was non-neutral. Non-neutral in EmotionLine refers to Joyful, Mad, Powerful and others. In the CARER dataset, 66 purchases happened on the emotional state which is Joy, Sadness, Fear, Anger, and Surprise while there is no record of neutral emotion. In the GoEmotion dataset, 251 Neutral emotions have been recorded for purchases and 67 purchases occurred while users had non-neutral emotions. In GoEmotion, Non-neutral emotions are Anger, Fear, Joy, Nervousness and Sadness. And lastly, in EmotionPush, 31 purchases were recorded in a neutral emotional state and only 3 emotional purchases had happened. In EmotionPush non-neutral emotions are Joy, Anticipation, Tired, Anger Fear and Sadness.

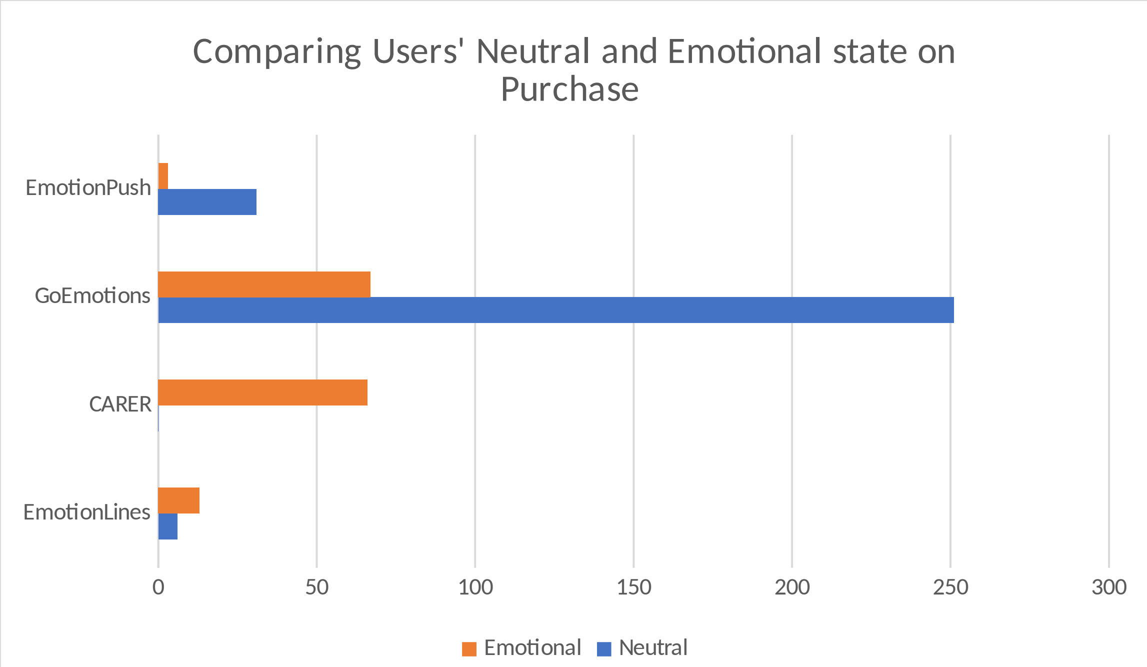


Figure 5.12 Comparing Users' Neutral and Emotional State on Purchase Intention

5.4 Hypothesis Testing

This section presents our hypothesis as follows:

Ho: There is no relation between user emotion to their online buying decision-making.

H1: User emotions play a significant role in online purchasing decision-making.

There are similarities between these four datasets such as having short sentences, having corresponding chat styles of conversation, and being labelled by basic emotions. However, there are some differences as well such as the source of each dataset which varies. Due to these differences, we test our hypothesis on each dataset separately.

Rejecting the alternative Hypothesis, because of the result and comparing the histograms in our datasets.

5.4.1 EmotionLines

Reject the alternative hypothesis, because the dataset shows Neutral as the top two emotions which have an impact on purchase intention. Although Joy is the first emotion that has an impact on purchase intention Neutral is the second and mad is the third one. Moreover, Table 5.2 and figure 5.6 show that the total number of neutral emotions is six and the number of non-neutral emotion are thirteen. Therefore, we cannot accept the alternative hypothesis and must reject it.

Table 5.10 EmotionLines vs. Purchase Intention by percentage

Count of Emotion	Column Labels		
Row Labels	No	YES	Grand Total
Neutral	16.67%	83.33%	100.00%
Non-neutral Emotion	7.69%	92.31%	100.00%
Grand Total	10.53%	89.47%	100.00%

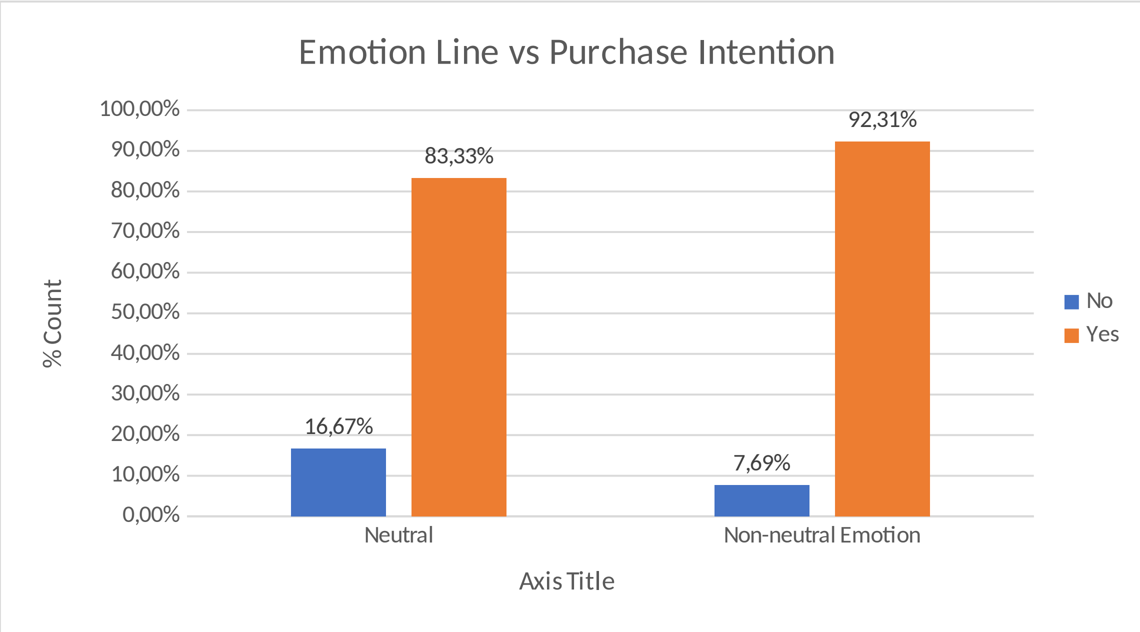


Figure 5.13 EmotionLines vs. Purchase Intention PivotChart

Table 5.11 EmotionLines & Purchase intention Crosstabulation

Emotion * Purchase intention Crosstabulation					
			Purchase intention		
			No	Yes	Total
Emotion	Neutral	Count	1	5	6
		% within Emotion	16.7%	83.3%	100.0%
	Non-neutral Emotion	Count	1	12	13
		% within Emotion	7.7%	92.3%	100.0%
Total		Count	2	17	19
		% within Emotion	10.5%	89.5%	100.0%

Table 5.12 EmotionLines Chi-square Tests

Chi-Square Tests					
	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.351[a]	1	.554		
Continuity Correction[b]	.000	1	1.000		
Likelihood Ratio	.329	1	.566		
Fisher's Exact Test				1.000	.544
N of Valid Cases	19				
a. 2 cells (50.0%) have an expected count of less than 5. The minimum expected count is .63.					
b. Computed only for a 2x2 table					

Conclusion

The P-value (0.554) is more than the level of significance (0.05). Therefore, we retain the null hypothesis and conclude that there is no relationship between emotion and purchase intention. In other words, emotion does not influence purchase intention.

5.4.2 CARER

We were unable to run the Chi-squared test on this dataset. The big difference between this dataset and the other three is that this dataset does not have the Neutral label as a dataset and has Others as the emotion which is zero in our result, however, Joy is 32 and Sadness is 14. Table 5.1 also shows 0 as Neutral emotion or others and 66 as Non-neutral emotion.

5.4.3 GoEmotion

Reject the alternative hypothesis, because the dataset shows Neutral is the predominant emotion in purchase intention with the number of 251 compared to Joy with 24 and Anger with 21. Table 5.1 also shows the Neutral emotion with 251 and non-neutral emotion with 67. This dataset shows Joy still plays a big role, after neutral, in purchase intention. This is the similarity between this dataset and EmotionLines and CARER.

Table 5.13 Go-Emotion vs. Purchase Intention by Percentage

Count of Emotion	Column Labels		
Row Labels	No	YES	Grand Total
Neutral	29.13%	70.87%	100.00%
Non-neutral Emotion	51.52%	48.48%	100.00%
Grand Total	34.56%	65.44%	100.00%

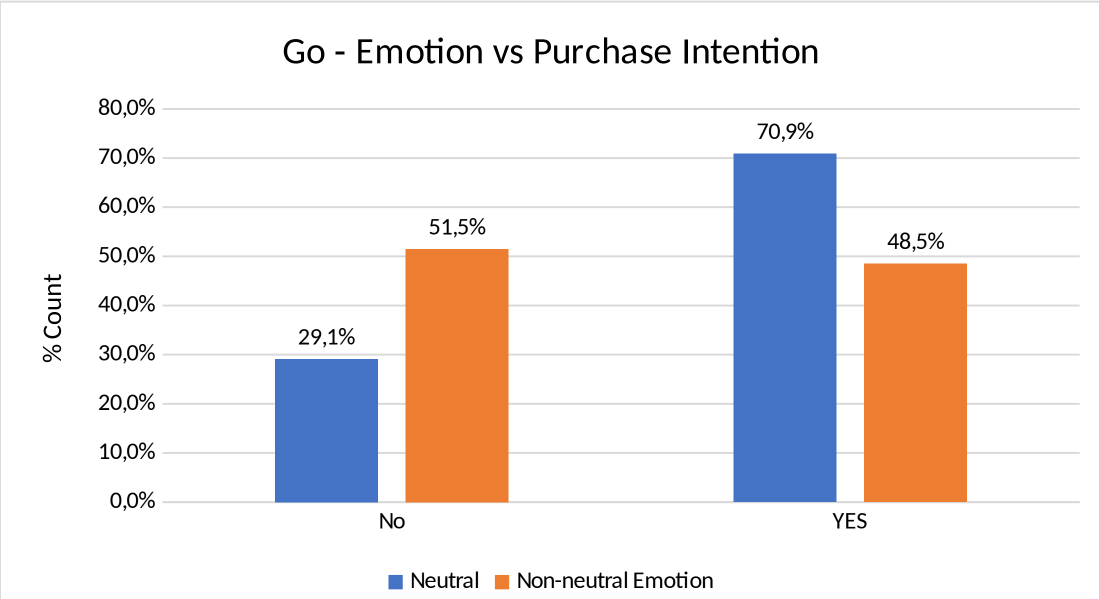


Figure 5.14 Go-Emotion vs. Purchase Intention PivotChart

Table 5.14 GoEmotion & Purchase Intention Crosstabulation

Emotion * Purchase Intention Crosstabulation					
			Purchase Intention		
			No	YES	Total
Emotion	Neutral	Count	30	73	103
		% within Emotion	29.1%	70.9%	100.0%
	Non-neutral Emotion	Count	17	16	33
		% within Emotion	51.5%	48.5%	100.0%
Total		Count	47	89	136
		% within Emotion	34.6%	65.4%	100.0%

Table 5.15 Go-Emotion Chi-Square Tests

Chi-Square Tests					
	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	5.539[a]	1	.019		
Continuity Correction[b]	4.594	1	.032		
Likelihood Ratio	5.358	1	.021		
Fisher's Exact Test				.022	.017
N of Valid Cases	136				
a. 0 cells (0.0%) have expected count of less than 5. The minimum expected count is 11.40.					
b. Computed only for a 2x2 table					

Conclusion

The P-value (0.19) is more than the level of significance (0.05). Therefore, we retain the null hypothesis and conclude that there is no relationship between emotion and purchase intention. In other words, emotion does not influence purchase intention.

5.4.4 EmotionPush

Rejecting the alternative hypothesis this dataset shows Neutral as the predominant emotion in purchase intention. Neutral has the number of 31 and the second emotion is Joy with 3 purchase intentions. All the other emotions combined have 0 purchase intention. Table 5.1 shows the comparison of 31 for Neutral Emotions and 3 for Non-neutral emotions. This dataset also shows Joy plays an important role in purchase intention.

Table 5.16 Emotion Push vs. Purchase Intention in Percentage

Count of Emotion	Column Labels		
Row Labels	No	YES	Grand Total
Neutral	18.57%	81.25%	100.00%
Non-neutral Emotion	33.33%	66.67%	100.00%
Grand Total	20.00%	80.00%	100.00%

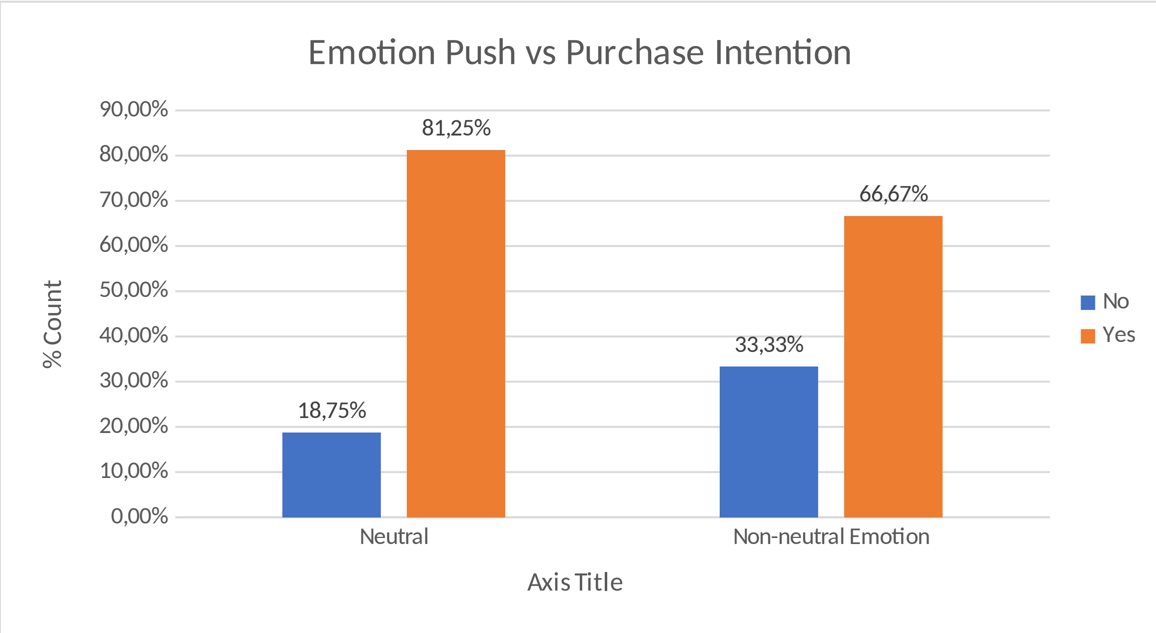


Figure 5.15 Emotion Push vs. Purchase Intention PivotChart

Table 5.17 Purchase Intention & Emotion Crosstabulation

Purchase intention * Emotion Crosstabulation

			Emotion		
			Neutral	Non-neutral Emotion	Total
Purchase intention	No	Count	6	1	7
		% within Purchase intention	85.7%	14.3%	100.0%
	Yes	Count	26	2	28
		% within Purchase intention	92.9%	7.1%	100.0%
Total		Count	32	3	35
		% within Purchase intention	91.4%	8.6%	100.0%

Table 5.18 EmotionPush Chi-Square Tests

Chi-Square Tests					
	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.365[a]	1	.546		
Continuity Correction[b]	.000	1	1.000		
Likelihood Ratio	.324	1	.569		
Fisher's Exact Test				.499	.499
N of Valid Cases	35				
a. 2 cells (50.0%) have an expected count of less than 5. The minimum expected count is .60.					
b. Computed only for a 2x2 table					

Conclusion

The P-value (0.546) is more than the level of significance (0.05). Therefore, we retain the null hypothesis and conclude that there is no relationship between emotion and purchase intention. In other words, emotion does not influence purchase intention.

5.4.5 Summary

In this section, we tested our hypothesis with the four datasets that we have. The reason for testing this hypothesis separately is that these datasets have been generated from different sources of content, although there are similarities too.

We rejected our alternative hypothesis in EmotionLines, GoEmotion and EmotionPush datasets.

Comparing all four datasets shows that although Joy is not the first emotion that has an impact on purchase intention, however, it is always the most important after the Neutral emotion. This finding has similarities with our finding in the systematic literature review which notes positive mood has an impact on purchase intention.

5.5 Synthesis of the Findings

The systematic literature review (Section 2.6) showed that there has been research on customer purchase intention service on chatbots (Jiang et al., 2022; Siripipatthanakul et al., 2021). They have found that security, reliability, having an enjoyable chatbot and intimacy have a positive impact on users to chat more with the chatbot and thus increase the purchase intention. Moreover, having positive emotions by reading product reviews as well as personalized ads could also help to make a purchase (Grigorios et al., 2022; Guo et al., 2020). Our focus, however, in this research was specifically on the user's emotional state while having the intention to purchase and finding out whether there are specific emotions that have influenced more on making a purchase or not. We found that Joy has an impact on purchase intention in a noticeable amount of time however it was not the predominant emotion and Neutral played an even bigger role when people have the intention to purchase. Figure 14 compares our four datasets based on neutral and non-neutral states and shows the big record of the neutral emotions on each dataset. CARER dataset didn't have neutral as an emotional option. Therefore, there is no certainty about an emotion that plays the biggest role all the time. The big challenge that we had during this research was the large number of Neutral emotions in the chats. Because contains two meanings. First, is that people who identified this emotion for each sentence were instructed that if they are not 100 per cent sure about the sentence's emotion, they should use Neutral as the identified emotion. Second, if the chat includes more than one emotion and none of them are the main emotion of the sentence, then Neutral is the correct answer. Another reason for having a large number of Neutral is having short sentences with only a few words, therefore, it makes it difficult to understand the correct emotion, and finally, identify only the basic emotions, such as Joy, Sad and Anger.

5.6 Summary

This thesis reports a research project regarding the impact of emotions on users' intentions on chatbot services. The inspiration behind this research is that chatbot usage has increased substantially in the past few years by websites and customer service companies. The focus of chatbot service improvement was on understanding the users' requests in an informative way however comprehending the user's emotions behind the chat was the part that was missing from the chatbot improvement in the previous research. During the systematic literature review, we found out that there was research on e-commerce websites regarding the factors that have an impact on users' purchase intention on e-commerce websites, such as trustworthiness, positive comments on products or website user-friendliness. However, there was no specific research, to the best of my knowledge, that worked on the impact of emotions on users' purchase intention on chatbots.

Understanding users' emotion during a chat session with a bot, improve the quality of the chat and persuade the user to chat more with the bot and return to chat again. In customer service companies having users communicate with bots will reduce operational costs and help to serve more people at a time as a bot can communicate with multiple people at the same time. Moreover, understanding the user, and then finding the right time to offer a sale, could lead to more sales. One of the ways to understand the right time is to find out the user's emotional state while chatting. The question here is which emotion has more impact on purchase decision-making.

To find out if users with particular emotions have more intention to purchase, we formed a hypothesis and collected data to test our hypothesis. There were four datasets in the form of chat collected and relevant emotions for each chat were extracted. Our result contributes towards understanding which emotions have more impact on purchase intention. This could help e-commerce website builders as well as customer service companies and developers to have attention to detect, comprehend and analyse users' emotions while they chat or communicate with e-commerce websites as it would help the user feel more comfortable and understood by the system which helps to communicate more and give more chance of making a purchase.

After testing our hypothesis on our four datasets, we rejected the null hypothesis on CARER and rejected the alternative hypothesis in EmotionLines, GoEmotion and Emotionpush. Moreover, we found out that Joy always is part of the top two emotions that have an impact on purchase intention.

CHAPTER SIX: Discussions & Conclusions

In this crucial chapter, we embark on a comprehensive exploration of our research findings, their implications, and the paths that lie ahead for our study on "The Effects of Stress and Chatbot Services Usage on Customer Intention for Purchase on E-Commerce Sites." This chapter serves as the culmination of our investigative journey, weaving together the threads of our research aim, objectives, hypothesis results, and the broader significance of our study. Our aim in this chapter is to provide a thorough understanding of the implications of our research and to offer practical recommendations for both academic and industry stakeholders.

6.1 Introduction

In Chapter 1, we set out the primary aim of this research, which is to identify and categorize potential buyers through the use of automated chatbots, enabling the timely presentation of appealing offers. This approach holds the promise of enhancing businesses' sales conversion rates and subsequently increasing their profitability. Furthermore, such a strategy offers the added benefit of reducing labour costs for businesses, as they would no longer need to engage in protracted sales discussions with customers. This research journey aligns with the aspirations of both e-commerce platforms and customers, aiming to streamline and enhance the online shopping experience for all parties involved.

Chapter 2 was dedicated to an extensive literature review that aimed to unearth pertinent research in the sphere of our research interest. This meticulous exploration played a pivotal role in our academic journey, enabling us to refine our research focus and cultivate a profound and multifaceted comprehension of the subject matter at hand. As we traversed through the diverse landscape of existing studies, this review served as a foundation upon which we could build our research framework. It allowed us to discern the prevailing trends, key findings, and the evolving discourse surrounding customer purchase intention in e-commerce, with a special emphasis on the role of chatbots. Beyond its foundational role, the literature review functioned as a radar, skillfully detecting gaps and fissures within the current body of knowledge. These identified voids represent not only areas ripe for further investigation but also opportunities to contribute novel insights to the field. The systematic exploration, guided by rigorous scholarly methods, was instrumental in constructing a comprehensive understanding of the factors that influence customer purchase intentions within the dynamic landscape of e-commerce. With each revelation, we found ourselves one step closer to unravelling the complex interplay between stress, chatbot services, and customer behaviour.

In Chapter 3, we shared our research approach and the steps we took in our experimental study. Think of this chapter as the blueprint of our research. We introduced the research pyramid as our guiding framework, explaining how it structured our study. We also described our experiment's design and our strategy for gathering and analyzing data. This chapter was essential in laying the groundwork for our actual research, providing you with a solid understanding of our methodology before we dove into the practical aspects.

Chapter 4 was all about our experiment. We talked about how we planned it, what we aimed to achieve, how we set it up, the steps we followed, who took part, and any changes we made along the way. This chapter gave a detailed look into the planning and execution of our experiment, ensuring transparency in our research process.

Chapter 5 was where we presented and analyzed our research results. We went through each of our objectives and examined the data we collected for each dataset. We also discussed the results from our post-test-only control group for User's Neutral and Emotional State of Purchase Intention. Furthermore, we shared the outcomes of our hypothesis testing for each dataset and combined all our findings into a coherent synthesis. This chapter provided a comprehensive overview of our research outcomes, shedding light on the relationships we discovered and their implications.

In our research, an experiment was conducted to test the hypothesis we developed which suggests that user emotions play a significant role in online purchasing decision-making. To examine this, an experimental design with a positive approach has been chosen.
There are three objectives defined in this research. The first objective is to find databases that have been labelled by relevant emotions. The second objective is to identify the sentences, chat or utterances that shows an intention to purchase, and the third objective is to filter the chats that indicate purchase intention create a histogram and test our hypothesis. We could find four datasets (EmotionLines, CARER and GoEmotions, EmotionPush) which are labelled by basic emotions. From these four dataset sentences the words 'buy', 'purchase', or their synonyms were found and the emotional state of the person in that sentence.

EmotionLines shows users with Joyful, Neutral and Mad emotions have more intention to make a purchase. CARER indicates Joy, Sadness and Fear play a bigger role compared to other emotions in making a purchase. GoEmotion demonstrates that Neutral, Joy and Anger are the top three emotions that have effects on people's intention to purchase. EmotionPush shows Neutral emotion as the main emotional state of the user.
Although Joy seems to be always part of the top two emotions that have effects on people's intention to purchase, however, it is not always the first emotion.

In future work, this result can be improved by having more chat data that have been labelled by basic emotions. Moreover, detecting emotions in more depth and categorising them would help to have fewer emotions with Neutral labels which will give a more accurate result. In most research users were instructed to choose between the basic emotions (joy, fear, sadness, trust, anger, surprise, disgust, and anticipation) and if they were not able to find relevant emotion for a sentence, they were instructed to choose Neutral.

6.2 Research objectives: Summary of findings and conclusion

6.2.1 Find datasets that have been labelled by emotions;

6.2.1.1 Summary Finding

The datasets that we required had to have two specifications. First, they need to be in the format of short text conversational chats. Such as a messenger chat or tweets. And secondly, each chat needs to be identified by the relevant emotions. During our systematic literature review, we found four datasets that have the above specification and were suitable for our purposes. The first one was EmotionLines (Chen et al., 2019) which is the TV script for the Friends Series that has been labelled the basic emotions. The second one was the CARER (Saravia et al., 2018) which was constructed from English tweets to which users added emotional hashtags to them. The third one GoEmotions (Demszky et al., 2020) which contains 58K comments from Redits all labelled by the associated emotions. The Fourth one is EmotionPush (C. Y. Huang & Ku, 2018) which includes Facebook Messenger chats with their emotions identified.

6.2.1.2 Conclusion

In fulfilling the first objective of our research, which aimed to find datasets labelled by emotions, we conducted a meticulous search for datasets meeting specific criteria. These datasets needed to be formatted as short text conversational chats, such as messenger chats or tweets, and crucially, each chat needed to be annotated with relevant emotional labels. Our systematic literature review yielded four datasets that impeccably met these criteria: EmotionLines (Chen et al., 2019), CARER (Saravia et al., 2018), GoEmotions (Demszky et al., 2020), and EmotionPush (C. Y. Huang & Ku, 2018).

6.2.1.3 Recommendation

Based on our research findings, we observed that a significant number of sentences in our datasets were labelled as "Neutral" by users who were asked to identify emotions. This prevalence of "Neutral" labels can be attributed to the instruction given to users, encouraging them to select "Neutral" when they were unsure about the emotions expressed in a sentence. To improve the quality and granularity of our datasets, we recommend two key considerations:

1. Enhancing Emotion Labeling: To reduce the abundance of "Neutral" labels, future dataset creators and researchers should consider providing a more comprehensive list of emotions for users to choose from. Expanding beyond basic emotions to encompass a wider range of nuanced emotional states can lead to more accurate and descriptive emotion annotations. This, in turn, will contribute to clearer and richer data, enabling a deeper exploration of emotional nuances.
2. Handling Multiple Emotions: Additionally, researchers should be mindful of sentences that may convey multiple emotions simultaneously. Some sentences may evoke a blend of emotions, making it challenging to identify a dominant emotion. To address this, future research can explore methods for annotating and analyzing sentences with multiple associated emotions, allowing for a more nuanced understanding of emotional complexity.

By implementing these recommendations, researchers can enhance the quality and depth of emotion-labelled datasets, ultimately advancing the accuracy and richness of emotional analysis in various applications, including sentiment analysis and emotion detection.

6.2.2 Identify the sentences or utterances that have mentioned buy/purchase or show intention to purchase;

6.2.2.1 Summary Finding

To fulfil this objective effectively, we employed a meticulous approach. We focused on words with unambiguous purchase-related meanings such as "Purchase," "Buy," and "Procure." Additionally, we considered words with multifaceted interpretations like "get," "secure," "deal," and "gain," recognizing that these words might encompass expressions of intent to purchase.

Through this methodical process, we meticulously filtered the sentences within our datasets to identify those that genuinely conveyed the desire or intention to make a purchase. It is important to emphasize that this process requires a careful balancing act between words with explicit purchase connotations and those with broader semantic nuances. Our findings, therefore, represent a comprehensive and context-aware identification of sentences indicating an intention to purchase.

6.2.2.2 Conclusion

In our pursuit of identifying sentences or utterances expressing an intention to purchase within our datasets, we employed a meticulous observation method. This involved scrutinizing words with explicit purchase-related meanings such as "Purchase," "Buy," and "Procure," as well as words with multifaceted interpretations like "get," "secure," "deal," and "gain." Our diligent approach enabled us to filter and pinpoint sentences that genuinely conveyed the intent to make a purchase. These findings have been derived to the best of the researcher's knowledge and expertise, ensuring the accuracy and relevance of the identified sentences.

6.2.2.3 Recommendation

Our exploration highlighted a challenge inherent to this objective—words with multiple meanings in the English language. For instance, the word "Buy" may not exclusively signify the act of purchasing a good or service; it can also indicate scepticism or disbelief in certain contexts. To address this challenge, we recommend the development of more refined natural language processing algorithms or linguistic context analysis tools. These tools should be designed to discern the specific contextual cues and linguistic nuances that distinguish genuine purchase intent from other potential interpretations of such words. By advancing the accuracy of sentence identification, researchers can attain a deeper understanding of customer intentions to purchase, bolstering the effectiveness of sentiment analysis and related applications in e-commerce research.

6.2.3 Check the emotion that is associated with that sentence and create histograms based on that result.

6.2.3.1 Summary Finding

Our third objective revolved around assessing the emotions associated with sentences conveying purchase intention within our datasets and subsequently constructing histograms based on these results. Following a meticulous identification of sentences indicating emotional intent from our dataset, we proceeded to create four distinct histograms for each dataset, thereby segregating and visualizing the emotions associated with each sentence. These histograms were instrumental in evaluating our research hypothesis.

However, our findings revealed a divergence from our initial hypothesis, as we observed a lack of consistency in emotions across the histograms. Despite this, two noteworthy trends emerged: "Joy" and "Neutral" emotions consistently represented the most prevalent emotional states among sentences indicating a purchase intent.

Furthermore, we conducted chi-square tests on datasets including EmotionLines, GoEmotion, and EmotionPush, which led us to reject our alternative hypothesis. These statistical tests provided valuable insights into the relationship between emotions and purchase intentions within these datasets. Notably, the CARER dataset presented unique challenges, rendering us unable to test our hypothesis due to a notable absence of "Neutral" emotions within its dataset.

In essence, our rigorous data analysis allowed us to gain a deeper understanding of the emotional nuances surrounding purchase intentions within each dataset. While our initial hypothesis did not align with our findings, the prevalence of "Joy" and "Neutral" emotions highlights the complexity of emotional states in the context of purchase intent. Additionally, the chi-square tests underscore the significance of these findings in the broader landscape of emotion analysis and e-commerce research.

6.2.3.2 Conclusion

In our pursuit of the third objective, we meticulously constructed four distinctive histograms, each tailored to unveil the emotional underpinnings of sentences indicating purchase intention within our datasets. These visual representations were instrumental in providing a tangible understanding of the intricate relationship between emotions and the inclination to make a purchase.

As we ventured into hypothesis testing, a pivotal aspect of our research, our findings led us to a critical outcome—the rejection of our alternative hypothesis. This unexpected result served as a profound revelation, signifying the intricacy and variability inherent in emotional responses within the context of purchase intent. While our hypothesis did not align with our findings, it ignites the torch of curiosity, encouraging further exploration into the nuanced dynamics of emotions in consumer behaviour, particularly within the dynamic landscape of e-commerce. This research endeavour, marked by its challenges and revelations, offers a compelling invitation for future investigations, as it unravels uncharted pathways in the ever-evolving field of emotion analysis in the context of online shopping.

6.2.3.3 Recommendation

While our research illuminated valuable insights into the relationship between emotions and purchase intentions across different datasets, it also revealed inconsistencies in the labelling of emotions. These disparities, such as the presence of "Powerful" in EmotionLines and "Anticipation" in EmotionPush without counterparts in other datasets, underscore the need for standardized emotional labelling within datasets.

We recommend that future researchers and dataset creators consider adopting a common emotional labelling framework to ensure consistency and comparability across datasets. This framework should encompass a set of universally recognized basic emotions, allowing for a harmonized approach in emotion analysis research. By adhering to standardized emotional labels, researchers can enhance the reliability and robustness of their findings and promote cross-dataset comparisons, ultimately advancing our understanding of the intricate interplay between emotions and consumer behaviours in e-commerce. Additionally, this standardization can contribute to the development of more comprehensive and accurate emotion detection models, benefiting a wide range of applications beyond the scope of our study.

6.3 Recommendations (or implications or lessons learned)

Our research journey has illuminated several important implications and lessons that can guide future endeavours in emotion analysis and sentiment classification, particularly within the context of labelling datasets and analyzing emotional expressions. Here are key recommendations and insights gleaned from our findings:

6.3.1 Enhancing Emotional Labeling:

A substantial portion of phrases in our datasets were assigned the label "Neutral." This tendency is influenced by the guidance provided to labellers, which suggests choosing "Neutral" when emotions are unclear. To refine emotional labelling, we recommend expanding the emotional lexicon employed in labelling exercises. Encouraging the inclusion of a broader array of emotions beyond the basic set can empower labellers with a more diverse emotional vocabulary. This expansion can lead to reduced reliance on "Neutral" and result in more precise and comprehensive emotional annotations.

6.3.2 Navigating Multifaceted Emotions:

The complexity of human emotions is evident when phrases evoke multiple emotional responses simultaneously. This complexity challenges the identification of a dominant emotional tone. To address this issue, we propose embracing multi-label annotations in emotion labelling processes. This approach allows labellers to attribute multiple emotions to a single phrase, acknowledging the intricate nature of emotional experiences and enabling a more thorough analysis of emotional expressions.

6.3.3 Tackling Linguistic Ambiguity:

The English language frequently presents words with multiple meanings, introducing ambiguity into emotional labelling. For example, "Buy" can denote a purchase or convey scepticism. To address this linguistic challenge, we suggest developing advanced natural language processing algorithms and linguistic context analysis tools. These tools should be capable of discerning contextual cues and linguistic nuances, thereby distinguishing genuine purchase intent from alternative interpretations. This enhancement can significantly improve the accuracy of identifying phrases related to service or product purchases.

6.3.4 Ensuring Consistency in Emotional Labelling:

In our research, we identified inconsistencies in emotional labels across datasets, with certain emotions unique to specific datasets. To promote labelling consistency, we recommend advocating for the adoption of standardized emotional labelling frameworks across datasets. These frameworks should establish uniform emotional categories, facilitating cross-dataset comparisons. A shared set of universally recognized basic emotions can serve as a foundational reference point for consistent labelling.

Incorporating these recommendations into future research and dataset creation endeavours will elevate the precision and depth of emotional analysis. This, in turn, will drive advancements in emotion detection, sentiment classification, and their applications within the dynamic realms of language processing and e-commerce research.

6.4 Contribution to the Knowledge

This research makes a substantial contribution to our understanding of the interplay between emotions and online purchase intentions. It begins by formulating a testable hypothesis, aiming to ascertain the significance of emotions in shaping online purchase behaviour. To rigorously test this hypothesis, the research establishes an experimental design utilizing an observation method, a methodology meticulously detailed in Section 3.3.

An integral aspect of this research's contribution lies in its use of four diverse datasets from various sources. To conduct this study, the research adopts a Posttest-only Control-Group Design within the framework of a Quasi-experimental design (Section 3.3.5). This strategic selection facilitates a comprehensive exploration of the role of emotions across different datasets.

The research culminates in a detailed analysis of experimental results (Section 5.2.5) that provides invaluable insights into the relationship between emotions and online purchase intentions within each dataset. Noteworthy findings emerge: for instance, within the EmotionLine Dataset, non-neutral emotions such as "Joyful," "Mad," "Powerful," and others are associated with 13 purchase intentions, while the "Neutral" emotion corresponds to 6 purchase intentions. The CARER dataset notably lacks a specific "Neutral" label and reports 66 non-neutral emotions tied to purchase intentions.

Hypothesis testing results (Section 5.3) further enrich the research's contribution. These results indicate that "Neutral" emotions primarily influence purchase intentions. This observation aligns with findings from systematic literature reviews, potentially indicating a correlation with trust in e-commerce transactions, as noted by researchers such as Bhatt, Qalati, and Yen & Chiang in their respective studies.

However, the research introduces an intriguing dimension by identifying "Joy" as the second most influential emotion on purchase intentions, a finding absent from prior systematic literature reviews. This novel insight aligns with the significance of positive reviews highlighted by Guo et al. (2020) and the role of improved emotional engagement emphasized in M. Wang et al.'s (2021) research as factors influencing purchase intentions.

In sum, this research advances our comprehension of the intricate relationship between emotions and online purchase intentions, offering both confirmation and fresh perspectives. By amalgamating rigorous experimentation with nuanced data analysis, it enriches our knowledge of emotional dynamics in the e-commerce landscape, making valuable contributions to the field's ongoing evolution.

6.5 Self-reflection

The journey into the realm of chatbot performance and its interaction with users has been a fascinating and enlightening one. What initially piqued my curiosity was the escalating presence of chatbots across a diverse spectrum of websites, ranging from small platforms to the expansive domains of major customer service websites. This ubiquity of chatbots led me to delve deeper into their functionality, performance, and the intricate challenges they pose for both companies and users alike.

In this era of rapid advancements in Artificial Intelligence and machine learning, it became evident that understanding and deciphering the nuanced intentional states of customers held the key to elevating the capabilities of chatbots. While these bots may excel in processing data and providing information, they often grapple with the crucial aspect of comprehending the emotional and cognitive states of users during interactions.

The realization that enhancing a chatbot's ability to discern and respond to a user's emotional state could lead to more empathetic and tailored interactions was a pivotal moment in this research journey. The prospect of a chatbot adapting its communication style based on the user's emotional cues held immense potential. This potential extended beyond merely improving customer experience; it could be a catalyst for fostering enduring relationships between users and chatbots.

Such enhanced interactions, if harnessed effectively, could translate into a win-win scenario for both companies and customers. For businesses, the ability to convert these interactions into successful sales transactions represents a substantial benefit. It aligns with the ultimate goal of providing value to customers and driving business growth. For users, the prospect of more personalized and empathetic interactions with chatbots can significantly enhance their overall experience, making them more inclined to return and engage with these AI-driven assistants.

In essence, this self-reflective journey into the world of chatbots and customer interactions has underscored the pivotal role that emotions play in shaping the future of customer service and e-commerce. It has instilled a sense of purpose to explore innovative solutions that bridge the gap between technology and human emotions, ultimately striving for more empathetic and effective interactions in the digital landscape.

6.6 Study Summary

This research embarked on a comprehensive exploration of the intricate relationship between emotions, chatbot conversations, and their influence on purchase intentions. The study unfolded across multiple objectives, each contributing to a deeper understanding of these dynamic dynamics.

Firstly, the research formulated a hypothesis (Section 1.5) to scrutinize the role of emotions in shaping online purchase intentions. To rigorously test this hypothesis, a meticulous selection of datasets was imperative. Four distinct datasets were meticulously chosen (Section 4.3) from various research papers, each exhibiting resemblances to chatbot conversations. This step marked the inception of the research's primary objective.

Furthermore, the study recognized the significance of prior research in the field. Thus, a systematic literature review was conducted (Section 2.8) to identify relevant studies that explored factors influencing purchase intentions. Notably, the review highlighted the absence of emotion detection as a factor in these studies, underlining the research's pioneering approach.

The research proceeded to meticulously analyze these datasets, identifying sentences indicative of purchase intentions through an observation method. These sentences were meticulously filtered, forming distinct datasets aligned with the study's second objective.

As the research journey continued, the study ventured into the creation of histograms. These visual representations aimed to unveil the emotions associated with each chat and dataset, aligning with the study's third objective. This stage offered a deeper insight into the emotional nuances within chatbot interactions.

Ultimately, the research tested its hypothesis on each dataset (Section 5.3) to draw critical conclusions regarding the influence of emotions on purchase intentions. The results of these hypothesis tests were underscored by the application of chi-squared tests (Section 5.4), collectively rejecting alternative hypotheses across all datasets.

This research does not conclude without acknowledging its limitations and offering insightful suggestions for future directions. These considerations provide a foundation for further research endeavours in the realm of chatbots, emotions, and their impact on online consumer behaviour.

6.7 Limitations

6.7.1 Dataset Limitations

One of the primary limitations of our study was the reliance on datasets that exhibited similarities with chatbot conversations. While these datasets served as valuable proxies, they lacked the depth and authenticity of actual customer service chatbot interactions. Obtaining real chat histories between customers and chatbots in customer service scenarios would be ideal. Such data would provide a more accurate assessment of how customers engage with chatbots and the underlying emotions involved. Real-world customer service chats often involve complaints and technical queries, potentially leading to emotions such as anger, frustration, or disappointment. Analyzing these genuine interactions could shed light on how chatbots impact and influence customer emotions throughout the conversation, potentially offering insights into mood shifts as tasks are resolved.

6.7.2 Dataset Differences

Despite the utility of the selected datasets, they were not uniform in terms of emotional content. Variations in the presence and intensity of emotions across datasets introduced limitations. Some emotions were unique to specific datasets, complicating cross-dataset comparisons. Additionally, certain sentences within the datasets conveyed multiple or mixed emotions simultaneously, posing challenges in determining the primary emotion. This complexity often led to sentences being categorized as "Neutral," as discerning the predominant emotion was a formidable task. To enhance the quality of the purchase intention analysis, future research should focus on refining emotion identification methods, including the handling of mixed emotions.

6.7.3 Lexical Ambiguity

The English language's inherent complexity, including slang and words with multiple meanings, presented challenges in filtering sentences that genuinely conveyed purchase intentions. To address this limitation, future research could consider compiling comprehensive lists of purchase-related keywords and expressions, encompassing various linguistic nuances. Such resources would aid in improving the precision of identifying sentences indicative of purchase intent.

6.8 Future Directions

6.8.1 Comprehensive Customer Behavior Tracking

A promising avenue for future research involves the integration of chatbot interactions with comprehensive customer behaviour tracking. This approach entails deploying a chatbot equipped to engage with customers while simultaneously monitoring their actions on e-commerce websites. This tracking can be achieved using behaviour analytics tools like Hotjar, Fullstory, or Smartlook. By combining chatbot interactions with user behaviour analysis, researchers can gain a holistic understanding of how customers navigate e-commerce platforms. This multifaceted approach allows for the real-time assessment of customer emotions during chatbot interactions and provides insights into the actions users take in response to chatbot offers. Researchers can explore whether customers engage with offers, read more about products, add items to their Wishlist, or proceed to make purchases. This integrated approach offers a comprehensive view of user behaviour, emotional responses, and purchase intentions in the context of e-commerce.

In conclusion, while this study has made notable strides in exploring emotions, chatbot interactions, and purchase intentions, there remain avenues for future research to overcome limitations and delve deeper into the complex world of online consumer behaviour. By combining authentic customer service chat data, refining emotion identification methods, and adopting a holistic approach to behaviour tracking, researchers can unlock new insights and drive advancements in the field of e-commerce and chatbot technology.

References

Agung Ayu Puty Andrina, A., Jordan Kurniadi, C., Hendrika Kenang, I., & FCW Sutrisno, T. (2022). The role of technology acceptance model factors on purchase intention in e-commerce. *BISMA (Bisnis Dan Manajemen)*, *14*(2), 160–176. https://doi.org/10.26740/bisma.v14n2.p160-176

Akram, U., Junaid, M., Zafar, A. U., Li, Z., & Fan, M. (2021). Online purchase intention in Chinese social commerce platforms: Being emotional or rational? *Journal of Retailing and Consumer Services*, *63*(July), 102669. https://doi.org/10.1016/j.jretconser.2021.102669

Alfanur, F., & Kadono, Y. (2022). The effects of gender and age on factors that influence purchase intentions and behaviours of e-commerce consumers in Indonesia. *International Journal of Innovation and Learning*, *31*(4), 474–505. https://doi.org/10.1504/IJIL.2022.123178

Andrade, I. M. De, & Tumelero, C. (2022). Increasing customer service efficiency through artificial intelligence chatbot. *Revista de Gestao*, *29*(3), 238–251. https://doi.org/10.1108/REGE-07-2021-0120

Bell, S. (2009). Experimental Design. *International Encyclopedia of Human Geography*, 672–675. https://doi.org/10.1016/B978-008044910-4.00431-4

Bhatt, V. (2021). *MEASURING IMPACT OF FACTORS INFLUENCING TO CONSUMER BUYING INTENTION WITH RESPECT TO ONLINE*. *January*. https://doi.org/10.34218/IJM.12.1.2021.019

Boell, S. K., & Cecez-Kecmanovic, D. (2015). On being “systematic” in literature reviews in IS. *Journal of Information Technology*, *30*(2), 161–173. https://doi.org/10.1057/jit.2014.26

Brown, S., & Melamed, L. (2012). Experimental Design and Analysis. *Experimental Design and Analysis*. https://doi.org/10.4135/9781412984218

Chen, S. Y., Hsu, C. C., Kuo, C. C., Huang, T. H. K., & Ku, L. W. (2019). Emotionlines: An emotion corpus of multi-party conversations. *LREC 2018 - 11th International Conference on Language Resources and Evaluation*, 1597–1601.

Cheng, Y., & Jiang, H. (2022). Customer–brand relationship in the era of artificial intelligence: understanding the role of chatbot marketing efforts. *Journal of Product and Brand Management*, *31*(2), 252–264. https://doi.org/10.1108/JPBM-05-2020-2907/FULL/XML

D’Aniello, G., Gaeta, M., & La Rocca, I. (2022). KnowMIS-ABSA: an overview and a reference model for applications of sentiment analysis and aspect-based sentiment analysis. *Artificial Intelligence Review*, *55*(7), 5543–5574.

https://doi.org/10.1007/S10462-021-10134-9/FIGURES/2

Dachyar, M., & Banjarnahor, L. (2017). Factors influencing purchase intention towards. *Intangible Capital*, *13*(5), 946–966.

Demszky, D., Movshovitz-Attias, D., Ko, J., Cowen, A., Nemade, G., & Ravi, S. (2020). *GoEmotions: A Dataset of Fine-Grained Emotions*. 4040–4054. https://doi.org/10.18653/v1/2020.acl-main.372

Grigorios, L., Magrizos, S., Kostopoulos, I., Drossos, D., & Santos, D. (2022). Overt and covert customer data collection in online personalized advertising: The role of user emotions. *Journal of Business Research*, *141*(March), 308–320. https://doi.org/10.1016/j.jbusres.2021.12.025

Guo, J., Wang, X., & Wu, Y. (2020). Positive emotion bias: Role of emotional content from online customer reviews in purchase decisions [Article]. *Journal of Retailing and Consumer Services*, *52*, 101891. https://doi.org/10.1016/j.jretconser.2019.101891

Helm, J. M., Swiergosz, A. M., Haeberle, H. S., Karnuta, J. M., Schaffer, J. L., Krebs, V. E., Spitzer, A. I., & Ramkumar, P. N. (2020). Machine Learning and Artificial Intelligence: Definitions, Applications, and Future Directions. *Current Reviews in Musculoskeletal Medicine 2020 13:1*, *13*(1), 69–76. https://doi.org/10.1007/S12178-020-09600-8

Huang, C. Y., & Ku, L. W. (2018). EmotionPush: Emotion and Response Time Prediction Towards Human-Like Chatbots. *2018 IEEE Global Communications Conference, GLOBECOM 2018 - Proceedings*. https://doi.org/10.1109/GLOCOM.2018.8647331

Huang, M. H., & Rust, R. T. (2022). A Framework for Collaborative Artificial Intelligence in Marketing. *Journal of Retailing*, *98*(2), 209–223. https://doi.org/10.1016/J.JRETAI.2021.03.001

Jiang, K., Qin, M., & Li, S. (2022). Chatbots in retail: How do they affect the continued use and purchase intentions of Chinese consumers? *Journal of Consumer Behaviour*, *21*(4), 756–772. https://doi.org/10.1002/CB.2034

Jonker, J. (Jan), & Pennink, B. J. W. (Barteld J. W. (2010). *The essence of research methodology : a concise guide for master and PhD students in management science*. 171. https://books.google.com/books/about/The_Essence_of_Research_Methodology.html?id=1ogIADAkWtoC

Khoa, B. T. (2021). The Impact of Chatbots on the Relationship between Integrated Marketing Communication and Online Purchasing Behavior in The Frontier Market. *Jurnal The Messenger*, *13*(1), 19. https://doi.org/10.26623/themessenger.v13i1.2439

Kothari, C. R. (2004). Research Methodology: Methods and Techniques - C. R. Kothari - Google Books. In *New age international*. https://books.google.co.za/books?hl=en&lr=&id=hZ9wSHysQDYC&oi=fnd&pg=PA2&dq=research+methodology+cr+kotha

ri&ots=1tZfqCb_A0&sig=id8-r0V-rQOrlvuXjS9usC2K7Hw&redir_esc=y#v=onepage&q=research methodology cr kothari&f=false

Lakens, D. (2022). Sample Size Justification. *Collabra: Psychology*, *8*(1), 1–28. https://doi.org/10.1525/collabra.33267

Laroche, M., Li, R., Richard, M. O., & Zhou, M. (2022). An investigation into online atmospherics: The effect of animated images on emotions, cognition, and purchase intentions. *Journal of Retailing and Consumer Services*, *64*(January 2021), 102845. https://doi.org/10.1016/j.jretconser.2021.102845

Lo Presti, L., Maggiore, G., & Marino, V. (2021). The role of the chatbot on customer purchase intention: towards digital relational sales. *Italian Journal of Marketing*, *2021*(3), 165–188. https://doi.org/10.1007/s43039-021-00029-6

Mason, M. C., Zamparo, G., Marini, A., & Ameen, N. (2022). Glued to your phone? Generation Z’s smartphone addiction and online compulsive buying. *Computers in Human Behavior*, *136*, 107404. https://doi.org/10.1016/J.CHB.2022.107404

Mishra, S. B., & Alok, S. (2017). *Handbook of research methodology. Dimensions Of Critical Care Nursing*. *9*(1).

Mohamed Shaffril, H. A., Samsuddin, S. F., & Abu Samah, A. (2021). The ABC of systematic literature review: the basic methodological guidance for beginners. *Quality and Quantity*, *55*(4), 1319–1346. https://doi.org/10.1007/s11135-020-01059-6

Mukherjee, S. (2021). Sentiment Analysis. *ML.NET Revealed*, 113–127. https://doi.org/10.1007/978-1-4842-6543-7_7

Mukherjee, S. P. (2020). *A guide to research methodology: An overview of research problems, tasks and methods*. CRC Press, Taylor & Francis. https://web-p-ebscohost-com.ezproxy.cput.ac.za/ehost/ebookviewer/ebook/bmxlYmtfXzIxNDIyMTNfX0FO0?sid=ad96563b-626c-4eba-b2e3-774380f9da0f@redis&vid=0&format=EB&rid=1

Müller, A., Laskowski, N. M., Wegmann, E., Steins-Loeber, S., & Brand, M. (2021). Problematic Online Buying-Shopping: Is it Time to Considering the Concept of an Online Subtype of Compulsive Buying-Shopping Disorder or a Specific Internet-Use Disorder? *Current Addiction Reports*, *8*(4), 494–499. https://doi.org/10.1007/S40429-021-00395-3/TABLES/1

Okoli, C. (2015). A guide to conducting a standalone systematic literature review. *Communications of the Association for Information Systems*, *37*(1), 879–910. https://doi.org/10.17705/1cais.03743

Okoli, C., & Schabram, K. (2010). Working Papers on Information Systems A Guide to Conducting a Systematic Literature Review of Information Systems Research. *Working Papers on Information Systems*, *10*(2010). https://doi.org/10.2139/ssrn.1954824

Park, Y. S., Konge, L., & Artino, A. R. (2020). The Positivism Paradigm of Research. *Academic Medicine*, 690–694. https://doi.org/10.1097/ACM.0000000000003093

Peña-García, N., Gil-Saura, I., Rodríguez-Orejuela, A., & Siqueira-Junior, J. R. (2020). Purchase intention and purchase behavior online: A cross-cultural approach. *Heliyon*, *6*(6). https://doi.org/10.1016/j.heliyon.2020.e04284

Qalati, S. A., Vela, E. G., Li, W., Dakhan, S. A., Hong Thuy, T. T., & Merani, S. H. (2021). Effects of perceived service quality, website quality, and reputation on purchase intention: The mediating and moderating roles of trust and perceived risk in online shopping. *Cogent Business and Management*, *8*(1). https://doi.org/10.1080/23311975.2020.1869363

Rahman, M. F., & Hossain, M. S. (2022). The impact of website quality on online compulsive buying behavior: evidence from online shopping organizations. *South Asian Journal of Marketing*. https://doi.org/10.1108/sajm-03-2021-0038

Saravia, E., Toby Liu, H. C., Huang, Y. H., Wu, J., & Chen, Y. S. (2018). Carer: Contextualized affect representations for emotion recognition. *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, EMNLP 2018*, 3687–3697. https://doi.org/10.18653/v1/d18-1404

Setyawan, M. Y. H., Awangga, R. M., & Efendi, S. R. (2018). Comparison Of Multinomial Naive Bayes Algorithm And Logistic Regression For Intent Classification In Chatbot. *Proceedings of the 2018 International Conference on Applied Engineering, ICAE 2018*, *October*, 1–5. https://doi.org/10.1109/INCAE.2018.8579372

Siripipatthanakul, S., Nurittamont, W., Phayaphrom, B., & Nuanchaona, S. (2021). Factors affecting consumer's purchase intention of chatbot commerce in Thailand. *International Journal of Business, Marketing and Communication, 1*(3), 1–13.

Soares, A. M., Camacho, C., & Elmashhara, M. G. (2022). Understanding the Impact of Chatbots on Purchase Intention. *Lecture Notes in Networks and Systems*, *470 LNNS*, 462–472. https://doi.org/10.1007/978-3-031-04829-6_41/COVER

Tran, A. D., Pallant, J. I., & Johnson, L. W. (2021). Exploring the impact of chatbots on consumer sentiment and expectations in retail. *Journal of Retailing and Consumer Services*, *63*, 102718. https://doi.org/10.1016/J.JRETCONSER.2021.102718

Verma, S., Sharma, R., Deb, S., & Maitra, D. (2021). Artificial intelligence in marketing: Systematic review and future research direction. *International Journal of Information Management Data Insights*, *1*(1), 100002. https://doi.org/10.1016/J.JJIMEI.2020.100002

Wang, M., Sun, L. L., & Hou, J. D. (2021). How emotional interaction affects purchase intention in social commerce: the role of perceived usefulness and product type. *Psychology Research and Behavior Management*, *14*, 467–481.

https://doi.org/10.2147/PRBM.S301286

Wang, X., Lin, X., & Shao, B. (2022). How does artificial intelligence create business agility? Evidence from chatbots. *International Journal of Information Management*, *66*, 102535. https://doi.org/10.1016/J.IJINFOMGT.2022.102535

White, H., & Sabarwal, S. (2014). *Quasi-Experimental Design and Methods*. *8*.

Xiao, Y., & Watson, M. (2019). Guidance on Conducting a Systematic Literature Review. *Journal of Planning Education and Research*, *39*(1), 93–112. https://doi.org/10.1177/0739456X17723971

Yang, L., Xu, M., & Xing, L. (2022). Exploring the core factors of online purchase decisions by building an E-Commerce network evolution model. *Journal of Retailing and Consumer Services*, *64*, 102784. https://doi.org/10.1016/J.JRETCONSER.2021.102784

Yen, C., & Chiang, M.-C. (2021). Trust me, if you can: a study on the factors that influence consumers' purchase intention triggered by chatbots based on brain image evidence and self-reported assessments [Article]. *Behaviour & Information Technology*, *40*(11), 1177–1194. https://doi.org/10.1080/0144929X.2020.1743362

Yun, J., & Park, J. (2022). The Effects of Chatbot Service Recovery With Emotion Words on Customer Satisfaction, Repurchase Intention, and Positive Word-Of-Mouth. *Frontiers in Psychology*, *13*(May), 1–12. https://doi.org/10.3389/fpsyg.2022.922503

Zheng, Y., Yang, X., Liu, Q., Chu, X., Huang, Q., & Zhou, Z. (2020). Perceived stress and online compulsive buying among women: A moderated mediation model. *Computers in Human Behavior*, *103*, 13–20. https://doi.org/10.1016/J.CHB.2019.09.012

Appendices

Appendix A: EmotionLines

#	Utterance	Purchase intention	Emotion
1	Okay, alright, you buy me a soda, and then we're even. Okay?	Yes	Neutral
2	Hey, hey, you're my baby, and I can't wait to meet you. When you come out I'll buy you a bagel, and then we'll go to the zoo.	Yes	Joyful
3	Ok, so it's just because it was my table, I have to buy a new one?	No	Mad
4	What do you mean, like, buy it together?	Maybe	Neutral
5	Good, Pheebs. What'd you buy?	Yes	Neutral
6	These new kids, they never last. Sooner or later, they all...stop lastin'. Listen, uh, what do you say I buy you that cup of coffee now?	Yes	Neutral
7	Well, I gotta buy a vowel. Because, oh my Gawd! Who, would've thought that someday, Chandler Bing would buy me a drawer.	Yes	Joyful
8	Okay but that's why you have to buy it, so it can fulfil it's Christmas destiny, otherwise there gonna throw it into the chipper. Tell him, Joey	Yes	Mad
9	You say 'Thank you very much,' and then you buy me something pretty. Come on, we're gonna put are hands in this bowl, and we're gonna start squishing the tomatoes.	Yes	Joyful
10	Y'know what, you should like, you should buy a state and then just name it after yourself.	Yes	Joyful
11	I ah, will buy and wrap all of your Christmas gifts.	Yes	Joyful
12	Cause you're a little princess! \"Daddy, buy me a pizza. Daddy, buy me a candy factory. Daddy, make the cast of Cats sing Happy Birthday to me	Yes	Powerful
13	Oh no! That-that'll just bring me down! This was great! I mean I-I-I was great! This is a great day! Y'know what? I'm buying everyone coffee. All right? If someone would just grab my wallet, it's in my pocket.	Yes	Joyful
14	Well, I'm gonna get another espresso. Can I get you another latte?	Yes	Neutral
15	Well this, this is too much, I feel like I should get you another sweater.	Yes	Mad
16	You know, I uh, I couldn't help but overhear what you just said, and I think it's time for you to forget about Rose, move on with your life...how 'bout we go get you a drink?	Yes	Mad
17	Oh, great! Listen, oh I had to get you a whole new battery. I got you the best one I could, 'cause that's not where you want to skimp.	Yes	Joyful
18	Pete, can I get you something else?	Yes	Neutral

19	Wow, a year and a half ago I didn't even know I had a brother, and now I have a sister too. Okay. Okay. Stop it, don't. So, I gotta get you a gift now. Is there anything you need?	Yes	Joyful

Appendix B: CARER Dataset

#	Chat	Purchase Intention	Emotion
1	i feel ugly i m more inclined to wear ratty jeans and a sweatshirt than a beautiful dress though i might still wear a pair of heels around my house to boost my self esteem ever so slightly but i definitely won t bother to buy a new pair;	No	Sadness
2	i think its kind of taken us this long to build up a good inventory of sauces oils spices and other non perishables to feel like we have a chance at making something delicious without having to specifically go out and buy every single item in a recipe;	No	Joy
3	i really want to go buy some yardage of art gallery just to play with because it feels so amazing;	Yes	Surprise
4	i get into what it actually does i feel like everyone should buy it just because it smells amazing;	Yes	Joy
5	i just feel so discontent about my life these days;	--	Sadness
6	im starting to not buy the whole everything happens for a reason bit or god has a plan b c i feel that god is love and theres no way that he would torture me and other women like weve been tortured dealing w fertility issues;	No	Anger
7	i feel like i have reached a plateau where im not buying as much as i use to and feeling more satisfied with my wardrobe and personal style;	No	Joy
8	i think i was feeling vulnerable due to the stress of having to buy a new sewing machine and printer;	Yes	Fear
9	i feel like i should go to the supermarket and buy something totally delicious for dinner with the money my mother put in my account today;	Yes	Joy
10	i feel like even though i dont buy into societys ideas about what a woman should look like i am still constantly unhappy with myself;	--	Sadness
11	i find it hard to feel jolly when throngs of people around me are so lost in the fervor of getting stuff that they cant see their heart for the green in their wallet encouraged by the constant barrage and pressure from every angle to shop here and buy more;	--	Joy
12	i am still feeling a little remorseful that we didnt just break down and buy it;	Yes	Sadness
13	i have made a few sets of his and hers wedding rings recently and i always feel so honored to be asked to make what is probably the most personal piece of jewellery that anyone ever buys;	--	Joy

14	i saw a few pianos that were either newer cheaper or larger but there was always something missing that made me feel uncertain about buying them;	Maybe	Fear
15	i am not sure if we should buy more but my hubby and i are feeling pretty impressed;	Maybe	Surprise
16	i try to only buy fabrics that i would use in a project or that i feel are really fab;	Yes	Joy
17	i feel very lucky and it is nice to be able to buy some lovely resources for the little ones i care for;	Yes	Joy
18	i do buy synthetic pearls when i feel the need to and i use these for some of my more elegant jewelry and trinkets;	Yes	Joy
19	i began to feel agitated because i wanted to buy ewan some food and medicine before i left;	Yes	Anger
20	i feel ok and go out into the world to work buy food or just go for a walk;	Yes	Joy
21	i or lambrusco but the quality is so much higher than a lot of those wines that i feel this is a smart buy for those who like a little sweet and a little bubbly;	Yes	Joy
22	i feel pride that i don t have to buy a roll of quarters from the bodega on the corner and this feeling is the only thing that keeps me from being irate that our laundry room is oddly devoid of coin changer machines;	No	Anger
23	i had promised her i will buy their cupcake bt im feeling shy to face her n thn miss it;	Yes	Fear
24	i go shopping now i feel reluctant to buy things like that even though its really hard to resist the temptation;	No	Fear
25	i dont have to buy it in tubs which feels vile;	No	Anger
26	i feel louis vuitton took it up to the court and now on for instance ebay you cannot buy fake lv anymore well not on purpose that is;	No	Sadness
27	i remember feeling annoyed but also wondering if i shouldn t stop and buy something;	Maybe	Anger
28	i was challenged by the clip where richard gere gives julia roberts money to buy some pretty clothes she walks into an expensive boutique in her work clothes and the condescending staff refuse to serve her and leave her feeling humiliated;	--	Sadness
29	i or you are feeling adventurous you can buy k ji kin spores by mailorder and make your own kome k ji using the rice of your choice;	Yes	Joy
30	i want to seduce you into buying it without you feeling liked youve been conned or connived into it;	yes	Love
31	im feeling very hesitant about wanting to buy another house;	Maybe	Fear
32	i buy a glamorous dress i might feel like a glamorous person dittmar explained;	Yes	Joy
33	i could buy i just want to see if i could recreate a recipe in order to feel superior and pretentious just kidding;	Yes	Joy
34	i was buying clothes that made me feel uncomfterble just so i was accepted;	Yes	Joy
35	i know i can do it and in fact that i will but i feel terrified that the stories won t be as good as they could be and that any readers that i can actually convince to buy the book will read it and hate it and never want to read anything by me again;	Yes	Fear
36	i had a feeling i had them but decided to buy them anyway which was a dumb	Yes	Sadness

	move;		
37	i gotta say that i feel like i was suckered into buying the iphone s because i saw the ads on how cool siri was;	Yes	Joy
38	i buy books about people i feel are equally fucked up as i am or books about zen approaches to shitty situations;	Yes	Anger
39	i aware and concerned for everyone will give attention not only marriages and deaths but also with equal seriousness to the elderly woman who feels helpless because she does not know which oven to buy;	No	Fear
40	im going to help you in this so if you feel that regretful then buy me an ice cream the next time we see each other;	Yes	Sadness
41	i also hate the feeling of forcing my values onto others not celebrating not buying others gifts for the sake of not supporting consumerism;	No	Joy
42	i would buy it again because it makes me feel pretty and the smell is divine;	Yes	Joy
43	i hope that those of you who actauly found this and read it feel possibly inspired to go out and buy some of these items or even go through storage and see what clothes of yours your mom saved and that you still have a hope of fitting in and mix up your wardrobe for this summer and have a little fun;	Yes	Joy
44	i usually buy but makes me feel especially virtuous when i go the homemade route ice cream;	Yes	Joy
45	i sometimes feel shitty and guilty for buying into them without actively making any choices i am about as normative you can get in terms of the fashion blogosphere;	Yes	Sadness
46	i am actually considering buying them thats why i feel so unsure hehe;	Yes	Fear
47	i feel pleased too that i am supporting people with small businesses who work from home buying gifts that have been made with care and talent;	Yes	Joy
48	i feel that if you love cute little things and your budget allows you and you buy this you won t regret buying it as it s just too cute;	Yes	Joy
49	i feel like buy to play is the most accepted model by consumers at large;	Yes	Love
50	i am tired of feeling that we have to buy buy buy to make the holidays seem special;	No	Joy
51	im feeling exceptionally brave that day to tell the husband that i need to buy it because i like it and nothing else;	Yes	Joy
52	i searched long and hard for a bad review telling me that i shouldnt buy into something i feel so apprehensive about but i only found that people loved and swore by f;	No	Fear
53	i enjoy driving a brand new car i still feel pained whenever i think of what i would have achieved by investing the money i saved by buying a second hand car;	Yes	Sadness
54	i make a big deal out of yours i d like you to at least buy me a card so that i can feel special;	yes	Joy
55	i was so traumatised by the pestilence that i was feeling quite delicate and couldnt cook so we had to buy expensive and unhealthy convenience foods from the supermarket in order to avoid starvation;	Yes	Love
56	i find myself buying into and reacting to the conflicts of modern life more than i	Yes	Sadness

	did before and feeling more jaded;		
57	i was i might be buying stuff from there but i feel the clothes are too casual;	Yes	Joy
58	when my close friend was involved in an accident and passed away instantly he had gone to buy a new car and had asked me to wait at his home so that i could see his new car;	Yes	Sadness
59	im feeling disillusioned with buying cheap mass produced clothes;	No	Sadness
60	i feel like i am that damaged can of corn with the big dent on the side and the label half torn off at the grocery store that is off that everyone pushes to the side and no one buys;	No	Sadness
61	i think browsers are more comfortable in my booth if all my attention is not focused on them and they don t feel pressured to make a purchase;	No	Fear
62	i love the liz earle moisturizer it does really leave the skin feeling lovely but i think i will purchase the lighter version next time;	Yes	Love
63	i feel a bit more confident about them now so heres a gorgeous pair of cream amp lemon shorts i recently purchased in the warehouse sale for;	Yes	Joy
64	i very close with the founder its amazing to feel that a purchase is supporting artisans trying to find their way out of poverty;	Yes	Joy
65	i get to purchase the best fruit the shop gets to reuse their bags and i feel virtuous about walking out of the shop without a scrap of new plastic the bag in the picture is old and well loved;	Yes	Joy
66	i walked away feeling triumphant with my first purchase of new make up finally done;	Yes	Joy
67	i remember feeling so inadequate as i stood there and they thanked me because of your purchases;	--	Sadness
68	ill tell you what its about as soon as im sure then well talk about how you can purchase it without feeling that youre in any way supporting me or what i do;	Yes	Joy

Appendix C: GoEmotion

#	Text	Emotion	Purchase Intention
1	I do take Vitamin C, daily. I purchased some probiotics yesterday. Hope those will help.	Neutral	yes
2	Including the fact that once I pirate something, i usually will purchase it later on either through frustration / poor quality/ actually loving the product / etc	Neutral	yes
3	Ah, I've only been for music and didn't purchase much else. I figure it would have the downtown markup though.	Neutral	No
4	The mango pods I purchased in New Zealand gave me a crazy headache but other flavours did not.	Neutral	Yes
5	Just made my first robocough purchase. Glad I used the website	Non-neutral Emotion	Yes
6	Bitch real man just panicking purchases a m82 barret..Now excuse me while i hide from my wife for the next month.	Non-neutral Emotion	Yes
7	I've seen [NAME] at the bars in Huntington a couple times and every time I see her I buy her a drink.	Neutral	Yes
8	If you buy a membership for yourself and your friends you can easily buy tickets to most games.	Neutral	Yes
9	I THINK ITS TIME TIME TIME YEAAAAA ITS TIME TO buy A FUTON !!!!!!	Neutral	Yes
10	That's it. I use a puff but my BF won't, so I'm always buying body wash for him about 3x as often.	Neutral	Yes
11	This game like 30 dollars on Humble Bundle on PC. When it goes down again (sale has expired) I'll try to buy it again.	Neutral	Yes
12	Itâ€™s a way of recognizing someoneâ€™s comment/post. Itâ€™s basically a thing that you buy for someone to help support reddit.	Neutral	yes
13	You could buy a used car for the price of those shoes!	Neutral	yes
14	yeah, but they think taking care is buying dinner and taking me on trips. I want money to spend on whatever I want.	Neutral	yes

15	Is L.A. Noire any good? I've been thinking about buying it lately.	Neutral	yes
16	mom can you give me money? to buy [NAME]? yeeees. actually buys relief pitcher like a boss ottavino time	Neutral	yes
17	Itâ€™s amazing how buggy this game is. Itd [NAME] buying a new car with most of the parts broken. We will fix it eventually.	Neutral	yes
18	Real paying customers never need to remind you of that fact. Tresspass her out of your shop, she wasn't going to buy anything anyway.	Neutral	No
19	Ok, so if I was to start what package/expansions do you suggest I buy ?	Neutral	yes
20	>not to a non negligible extent buy a thesaurus	Neutral	no
21	Your entire argument is undermined by how triggered you are. Also buy a thesaurus. And not all words have power all words have meaning.	Neutral	yes
22	I mean, one has to do the research. buying a lemon doesn't mean that having a car is "worthless".	Neutral	no
23	Ion know but it would be better for you to just buy some trim and make them yourself, its not that hard and you can dose it	Neutral	yes
24	Lilo and Stitch is one of my favorites. I really want to go buy a stuffed Stitch to hug now.	Neutral	yes
25	The man the myth the legend [NAME] has me seriously thinking about buying a new jersey with his name on the back	Neutral	yes
26	We aren't even buying it's loans and still nobody has been signed	Neutral	no
27	When you make excuses about what you're buying, you're the one calling attention to it.	Neutral	yes
28	**You don't have to buy it.** Just like that probably because it's still true lol.	Neutral	no
29	Your mom did you a favor; now there is one less of â€œus kidsâ€□ that will be buying mom a house and taking care of her.	Neutral	yes
30	Makes sense, but I imagine if they wanted the land that badly theyd just buy it off him	Neutral	yes
31	buy YouTube Likes	Neutral	yes
32	Man that's making me reconsider not buying his jersey...	Neutral	no
33	Just buy a load of old iPhone back covers in	Neutral	yes

	China.		
34	This guy isn't getting laid lmao he's tipping girls and buying them things in exchange for webcam sessions and videos.	Neutral	yes
35	I buy VHS, DVD and Blu-ray. I have a huge collection.	Neutral	yes
36	Imagine buying a product, then burning it in protest	Neutral	yes
37	Not in Oregon anymore. They raised the legal age to buy smokes to 21, which, as a smoker, I think is a great idea.	Neutral	no
38	Because nobody in their right mind would ever buy it	Neutral	no
39	Most people buy them new because the risk of them being involved in some sort of accident is just too high.	Neutral	no
40	If Studio MDHR did this, I'd buy it.	Neutral	yes
41	I wish I could buy one! So cute!!!	Neutral	yes
42	Imagine we hadn't spent money on Barkley, Drinkwater, and Bakayoko. The money there would've been enough to buy someone like Isco	Neutral	no
43	Id buy those shoes and walk in the dirtiest places just to piss [NAME] off.	Neutral	yes
44	Iâ€™ll buy every colourpop collab she does. Good formulas. I love supporting [NAME] and itâ€™s AFFORDABLE. What more do u want? ðŸ˜‚	Neutral	yes
45	Just donâ€™t buy a sports car and youâ€™ll be fine	Neutral	no
46	Now that you live alone you don't have money left to buy a dishwasher	Neutral	no
47	Hidilly ho there neighbourino now stop swearing you [NAME] damn cunt I'm buying my son GTA V	Neutral	no
48	You can buy the full "girlfriend experience" with a hooker for way less than 13k lmao.	Neutral	yes
49	I prefer buying the winner chests and holding on to the Godlike chests until a skin I want is in it.	Neutral	yes
50	Hay girls, if you where make-up, you can't buy me chicken tendies.	Neutral	no
51	When you buy the dog you get a lot of training to go with it and it's usually then further trained to specifically protect the person.	Neutral	yes
52	this is def an ad to buy doritos, but ill be	Neutral	yes

	goddamned if its not a pretty cool recipe		
53	Sitting here, waiting for the price to drop so i can buy more. I guess it's not gonna happen.	Neutral	yes
54	best: buy flowers because you want to make you SO smile worst: keep going because love is what matters not the issues	Neutral	yes
55	That's the exact person who would buy one of those	Neutral	yes
56	they dont have to buy all of it.	Neutral	no
57	Did you accidentally buy the Australian model of the camera?	Neutral	yes
58			
59	Yes, [NAME] doesn't like situations where he can't buy a victory.	Neutral	no
60	Go buy groceries and don't spend another dime for an entire week. Please....	Neutral	yes
61	Lovely places to buy from but very hard to get a good price as a seller because of their high rents (and bargaining expertise!)	Neutral	yes
62	What does that do with having the buyer sign the title?	Neutral	yes
63			
64	I report these every time they appear on the buy/swap/sell groups.	Neutral	yes
65	[NAME], buy me dinner before you go to poundtown on us.	Neutral	yes
66	Aaaaand already at -1.5 @ BOL. I'm going to wait to see if it comes back down, or imma buy the hook.	Neutral	yes
67	Money can't buy me happiness...	Neutral	no
68	I'm not a real estate guy, but isn't it normal for rich people to buy nice houses in nice areas?	Neutral	no
69	The walls are repainted anyway every few years, so if you buy the paint you want, they will even do it for you with that.	Neutral	yes
70	Eh, its up to you.. but Im not buying your girlscout cookies just because some of the troop drowned.	Neutral	no
71	I think they're seasonal? I'm not sure, I don't buy squash so I just go by our PLU book	Neutral	no
72	Depends on what you want to do, but I'd buy This	Neutral	yes
73	Why not though? Not enough buyers?	Neutral	yes
74	Not if I legalize it. Then you can buy it.	Neutral	yes

75	Mate I was buying porn mags from my local coop at 12, I don't see why trading standards makes such a fuss over a lotto ticket	Neutral	yes
76	I do! I buy 5-blade Dorcos. I'll never go back to razors marketed to women.	Neutral	yes
77	I do actually, everytime I buy vegetable or sunflower oil I get that massive plastic jug thing that the supermarket sells its only like Â£2.50/Â£3.50 depending where you go	Neutral	yes
78	Your LPT is to save money by not buying cords but instead stealing them from work?	Neutral	no
79	But they're here to ~~buy properties for their family!!!~~ I mean study, they're here to study!	Neutral	yes
80	I think the real incels are the ones that were willing to buy her yoga pants, most likely her followers.	Neutral	yes
81	Keep playing â€˜18, save your money on â€˜19 and go buy beer.	Neutral	yes
82	ive been looking at buying this exact knife for like 6 months.. how is it?	Neutral	yes
83	If I buy too much local icecream from the icecream store, Dryers will go bankrupt! (????) These people are so desperate.	Neutral	yes
84			
85	For me it's more about making my personal appearance a hobby more than just buying expensive stuff to have it	Neutral	no
86			
87	Somewhere to buy a hella warm winter coat? #polarvortex	Neutral	yes
88	I would say there is a very good chance he did not buy these drugs at a pharmacy.	Neutral	yes
89	Nah eats the heads when heâ€™s finished with them. I punt them so I can buy fresh meat.	Neutral	yes
90	most conservatives have been pissed at cities in Minnesota raising the age to buy tobacco, I guess i'm a little confused on what you are talking about.	Neutral	no
91	Instead we'll buy players like Drinkwater, Bakayoko and Zappacosta.	Neutral	yes
92	where else would one buy the ingredients from? Like are their dozens of ice cream suppliers?	Neutral	
93	Did you buy a new saddle as well. Also need to	Neutral	yes

	go to settings and set as default or make it active.		
94	Man, I canâ€™t wait to buy cannabis from [NAME].	Neutral	no
95	TBH I would definitely wear this with my denim jacket, but I wouldn't buy a huge lathe and carving tools to make it.	Neutral	no
96	Cucumber for some reason always seems darker to me. Maybe itâ€™s cause less people buy it so they sit there longer	Neutral	no
97	TIL when your fiancee steals 500 from you to buy products that harm you physically by being in the home due to allergic reaction you're controlling her.	Neutral	yes
98	Is it bad that I would actually probably buy that? Those come in handy for defrosting windows.	Neutral	yes
99	Maybe that's why she was trying to buy a firearm. To lead the fight against the alien invasion.	Neutral	yes
100	Iâ€™m this close to buying a tweezer and doing my own eyebrows but Iâ€™m fully aware itâ€™s the masculinity stopping me lmao.	Neutral	yes
101	No. 2 â€œItâ€™s a pornography store. I was buying pornography.â€□	Neutral	yes
102	Nothing wrong with pasta or bread. Stop buying bleached flour products and get whole grain.	Neutral	no
103	Canâ€™t buy a bucket...just one of those games	Neutral	yes
104	Good lord [NAME], just donâ€™t buy it	Neutral	no
105	The value of the knowledge from the books you could buy is priceless!	Neutral	yes
106	I quit soda about a month ago and this makes me want to go buy an entire 2-liter just to comfort myself	Neutral	yes
107	I get ya. If thinness was something I could buy I'd be flat broke by now	Neutral	no
108	Go buy some stand-offs. The stop the ladder from falling sideways.	Neutral	yes
109	Cough cough, r/gunners would likento buy you a drink for speaking the truth good sir.	Neutral	yes
110	Just. buy. A. Table. Itâ€™s got to be less work than... this monstrosity.	Neutral	yes
111	In 5 days bones would not be crusted over,sorry not buying it.	Non-neutral Emotion	no
112	Doordash pays less than minimum wage, no money even to buy cheesecake from the	Non-neutral Emotion	no

	cheesecake factory after paying rent and Bills ðŸ˜¥		
113	buying Bitcoin at it's peak is the equivalent of people buy Fyre festival tickets. I'm glad I did neither	Non-neutral Emotion	no
114	It's not cool that so many are going without pay and unable to make rent or buy groceries. Is a travesty that a manufactured crisis has come to this	Non-neutral Emotion	no
115	Mom will get sad. [NAME] still good. Hanging out with friends still good. Money buying foodie exp is still good.	Non-neutral Emotion	no
116	I'm sorry if this is Real but this sounds like something from r/thathappened But if it is Real then kudos and sÄ…d that the EK didnt buy you a ps4	Non-neutral Emotion	no
117	You're amazing. I'd buy it :)	Non-neutral Emotion	yes
118	I can only download games using SteamCMD at work at the moment, so yeah, glad I could buy it before the shutdown	Non-neutral Emotion	yes
119	Hahaha thanks for sharing that is simply amazing. You probably gave the buyer a good laugh too.	Non-neutral Emotion	yes
120	You can buy bitesize toad in the holes in Tesco. They are amazing. These look like they use hotdogs but I imagine would be almost as good.	Non-neutral Emotion	yes
121	Yesterday I remembered that this game existed and was happy that I waited and didn't buy into a game that would be dead in a month.	Non-neutral Emotion	no
122	Lol. Go astroturf r/politics. We aint buying her leftist bs here	Non-neutral Emotion	no
123	seriously... if he was going to play in LA he wouldn't do it with a 2 hour commute lol. he would just buy a mansion in LA	Non-neutral Emotion	yes
124	I mean, if I make it look like an accident, just think of all the ribs I can buy with the insurance money...	Non-neutral Emotion	yes
125	I suggest going to the food carts. buy some legal weed. Enjoy the bars. Go to Washington Park.	Non-neutral Emotion	yes
126	That must be it? Or that people buy carbon dioxide as plant food? I'm terrible at science and even I know it's not that simple	Non-neutral Emotion	yes
127	They'd probably just use it to buy up armies and	Non-neutral Emotion	yes

	navies for tyrants who oppress and reign with blood and horror or some shit.		
128	Colts fan here. [NAME] seems like a nice enough guy but, holy crap, terrible coach. buyer beware.	Non-neutral Emotion	yes
129	Right. The comments people buy gold for astound me. Iâ€™ve seen some dumbass comments get gilded then comments that deserve it get nothing.	Non-neutral Emotion	yes
130	Wow this was awful. What kind of audience do these morons have? I mean no one with the money to buy that junk would watch these fools	Non-neutral Emotion	no
131	That's ignorant as all hell. Tell them to buy their own.	Non-neutral Emotion	no
132	No. Spend all of it ASAP. Spend the evidence so you can get rid of it quickly and safely while also still being able to buy shit!	Non-neutral Emotion	no
133	Any food shortages will be caused by these idiots each buying 38 tins of beans a few days before we leave.	Non-neutral Emotion	no
134	Â£20 per child?! That is ridiculous! You canâ€™t buy much of anything for that! I am furious on your behalf!!	Non-neutral Emotion	no
135	Takes a lot less effort to just say â€œfuck off, buy your own.â€□	Non-neutral Emotion	no
136	They typically go bad before use. I can buy a plastic banana!	Non-neutral Emotion	yes
137		Non-neutral Emotion	
138	Not if ya delusional boi here buys it first	Non-neutral Emotion	no
139	Agreed, those who are waiting for their life-changing amounts to buy a home for their families just have to wait.. they are so selfish	Non-neutral Emotion	no
140	Iâ€™ll buy it i donâ€™t care	Non-neutral Emotion	yes
141	It makes me super fucking nervous edit: was able to buy temple at +1 fuck it lets ride	Non-neutral Emotion	yes
142	Even if itâ€™s available 24/7 on your new website 99% of it is ugly so people still wonâ€™t buy it.	Non-neutral Emotion	no

Appendix D: EmotionPush

#	Utterance	Purchase intention	Emotion
1	yeah i'd like to buy some clothes	Yes	Neutral
2	i'll buy things I know fit already	Yes	Neutral
3	But yeah you right, although I need to make a small investment in order to buy the case	Yes	Neutral
4	Also mfw with all the stuff I sold person_35 I can buy that location_18 supply set and still have a good chunk of money left over.	Yes	Joy
5	yeah went to buy things	Yes	Neutral
6	Didn't buy that top tho	No	Neutral
7	you should buy more emergency caffeine for exam	Yes	Neutral
8	Also should I buy this	Yes	Neutral
9	You should save that till you know what you need to buy for your dorm	No	Neutral
10	Then buy a pack for a dollar somewhere	Yes	Neutral
11	I need to grab a buyer lol	Yes	neutral
12	Also do you need anything? I'm going to wal mart to buy person-HL spray paint sometime today haha	Yes	Neutral
13	Can we buy one for someones birthday?	Yes	Neutral
14	Like we just got a voucher that we can exchange for a ticket the day of so if you buy we can sit together lol	Yes	Joy
15	where do we buy	Yes	Neutral
16	i can't go out and buy stuff even if i want to	No	Neutral
17	Ok perf I'm gonna go in a lil bit to the art store to buy some wire	Yes	Neutral
18	We should buy the boxes	Yes	Neutral
19	Time to buy xiv	Yes	Neutral
20	don't buy XIV	No	Neutral
21	i just want to buy	Yes	Neutral
22	Yo I might send you my CU store credit to give to person_208 if I buy his GC lot	Yes	Neutral
23	Yup. I'll clean it. You want it? Whom are you buying for?	Yes	Neutral
24	one of my friends needs to buy food from giant eagle so don't feel forced to come lol	Yes	Neutral
25	i also need to buy utensils	Yes	Neutral
26	Unfortunately no. I moved into my bf's straight from location_52. Didn't bring any furniture. I have been on the look out for it though. on the lafayette Buy and sell page	--	Neutral

27	best part-> we wouldn't need to buy a fucking thing	No	Joy
28	there are few people even looking to buy rn	Yes	Neutral
29	just buy a second charger omg	Yes	Neutral
30	I'll just buy	Yes	Neutral
31	I just talked to person_260 and chapter and she said she was gonna buy her own ticket to go and give me her voucher so I didn't want her to do that anymore....	Yes	Neutral
32	Did you buy 1 tin?	--	Neutral
33	Buy singles for the rest	Yes	Neutral
34	i end up buying things i dont need	Yes	Neutral
35	Oh, you buy them and keep them I believe	Yes	Neutral