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Research Article

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

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Abstract

In the rapidly evolving digital marketplace, customer service has become a critical factor influencing consumer behaviour. With the advent of Artificial Intelligence (AI), particularly chatbots, customer service companies are increasingly leveraging technology to enhance user experience. This study explores the relationship between customer emotions, detected during interactions with e-commerce chatbots, and their subsequent purchase intentions. Emotion detection within Human-Computer Interaction (HCI) is a vital area of research, as specific emotions, such as joy or frustration, can significantly impact marketing effectiveness and consumer decision-making. This research aims to understand how emotional responses to chatbot interactions can predict customer's intention to purchase, thereby offering insights for businesses to optimize their AI-driven customer service strategies. The study analyzes four diverse datasets – EmotionLines, CARER, GoEmotion, and EmotionPush – to identify emotion-labelled sentences indicative of purchase intention. Our findings reveal that Neutral and Joyful emotions are predominant in influencing customers' purchase intentions, highlighting the importance of understanding these emotional states in e-commerce settings. While Neutral emotion is most influential, Joy consistently plays a significant role in positive customer engagement. This research underscores the need for e-commerce businesses to focus on emotional intelligence in chatbots, enhancing customer experience and potentially driving sales. Future research directions include examining real chatbot-customer interactions to further understand the impact of AI-driven customer service on consumer emotions and behaviours.

Keywords

Artificial Intelligence, Chatbots, Customer Engagement, Customer Service, E-commerce, Purchase Intentions, User Emotions

1. Introduction

Customer service companies have shown significant interest in integrating Artificial Intelligence (AI) into their systems. A chatbot is an AI application with the ability to initiate a conversational session with a human partner, maintain, and handle a complex and nuanced conversation in natural language [1]. The primary reason businesses are keen on chatbots is their potential to reduce customer service costs and handle multiple users simultaneously [2].

Emotion detection in Human-Computer Interaction (HCI) has been a subject of research for over two decades [3]. Previous research indicates that certain emotions, such as anger, are particularly relevant in marketing. Anger suggests that the customer is engaged and has an optimistic outlook on the future, making it more likely to lead to action [4]. Therefore, understanding emotions and their significance in the human decision-making process can be beneficial for commercial

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entities, institutions, and organizations.

1.1. Previous Work

Research has been conducted on customer purchase intention with chatbots [5, 6]. It has been found that factors like security, reliability, an enjoyable chatbot experience, and intimacy have a positive impact on encouraging users to engage in more conversations with chatbots, consequently increasing purchase intentions. Additionally, experiencing positive emotions through product reviews and personalized advertisements can also influence purchasing decisions [7, 8].

1.2. Problem Statement

The rapid growth of companies' interest in utilizing chatbots in their customer service departments and the high expectations placed on chatbots to comprehensively address customer requests [9] have driven chatbot developers to enhance chatbot performance. Despite the progress made in improving chatbot efficiency in information detection, analysis, and user responses, emotion detection, particularly stress detection, is lacking in e-commerce chatbots. Implementing stress detection algorithms can empower chatbots to discern both explicit and implicit information from users. The absence of emotion detection in e-commerce chatbots may impact user engagement rates.

1.3. Aim and Objectives

The aim of this paper is to detect and classify potential buyers via automated chatbots to present offers at moments that would entice them to make a purchase. To achieve this aim, two main objectives have been established. The first objective is to identify datasets that have been labelled with emotions and pinpoint sentences that express an intention to purchase. The second objective is to assess the emotions associated with these sentences to test our hypothesis.

1.4. Hypothesis

1.4.1. Background

Several studies [10, 11] have identified a significant relationship between stress and compulsive buying. Since stress detection algorithms have recently been applied to microblogs [12, 13], it is reasonable to assume a connection between stressed users interacting with chatbots and their intention to make a purchase. Studies by [4] support this assumption, suggesting that certain emotions are likely to influence the decision-making process.

1.4.2. Null Hypothesis Ho

There is no relationship between user emotion and their online buying decision-making.

1.4.3. Alternative Hypothesis H1

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

2. Method

A quasi-experimental design is a type of experimental design that utilizes observational data to address research questions and causal hypotheses [14]. Quasi-experimental designs are often employed when it is neither possible nor ethical to randomly assign participants to treatment and control groups, or when it is impractical to do so. These designs can be used to investigate 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 correlated, but there is no causal relationship.

The ideal experimental design for our research would involve one or more controlled groups of customers to whom we offer a sale specifically and record their acceptance or rejection while observing their emotional state for our research. Unfortunately, we do not have access to such datasets. Consequently, we are unable to pretest our dataset. Due to our limitations, the only viable option for a true experimental design is to observe whether the purchase occurs in a neutral or non-neutral emotional state. Therefore, we compare these neutral and non-neutral emotional states.

The limitation of this study pertains to purchases labelled as "Neutral." All four datasets used in our research were compiled from previous studies. In these studies, individuals responsible for labelling each sentence with relevant emotions were instructed to select "neutral" emotions when they could not fully comprehend the emotional content of the sentence, when mixed emotions were present, when no predominant emotions were discernible, or when emotions were absent. Thus, a sentence labelled as "neutral" does not necessarily mean the sentence itself is neutral; it signifies that the emotional state of the sentence could not be conclusively determined. Moreover, we sought datasets resembling chatbot conversations, and these datasets consist mostly of short sentences, often lacking sufficient context to indicate a purchase. Consequently, there might be purchases with emotional content in the overall chat session, but such emotions cannot be attributed to individual sentences.

In our experimental design, we did not randomly select our datasets and purchase records but used the entire dataset.

3. Procedures

3.1. Data Collection

In our paper, we had four groups of datasets, each extracted from previous researchers who had made their datasets publicly available. These datasets met two critical criteria. First, they took the form of chat conversations generated from chat histories or a series of comments or tweets derived from the history of social media websites. Second, these datasets had been annotated with relevant emotions, including joy, sadness, anger, etc. Furthermore, the detected emotions in these datasets were attributed to humans, not another machine or software, ensuring the reliability of the emotion detection. During our literature review process, we identified four datasets that met these specifications: EmotionLines [15], CARER [16], GoEmotions [17], and EmotionPush [18].

Table 1. *Collected 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

3.2. Filtering Datasets Based on Purchase Intentions

3.2.1. EmotionLines

In the EmotionLines dataset, we had over 10,800 chat dialogues. Approximately 19 of them indicated an intention to make a purchase. Out of these 19 sentences, Neutral and Joyful emotions played the most significant roles, with Joyful having 8 instances, Neutral with 6, Mad with 4, and Powerful with 1 showing purchase intentions. Several sentences were identified with other emotions, making it unclear which precise emotion was associated with the sentence. However, this did not affect the overall result as the count remained at zero. The EmotionLines dataset indicated that Neutral, Joy, and Surprise appeared more frequently.

3.2.2. CARER

The CARER dataset contained over 11,300 tweets, which had been labelled with relevant emotions through hashtags by their authors. Our analysis revealed that 66 sentences exhibited an intention to engage in a transaction. Out of these 66 tweets, Joy played the most significant role with 32 instances of purchase intentions, followed by Sadness with 15 intentions to buy. Fear was the third with 10 intentions, Anger had 7, and Surprise had only 2. Similar to EmotionLines, tweets with unknown emotions were labelled as "others," and again, the count remained at zero.

3.2.3. GoEmotions

GoEmotion had over 211,200 comments from Reddit, with 318 of these comments indicating an intention to acquire goods or services. Neutral was the predominant emotion in this dataset, with 251 intentions to buy. Joy and Anger were close in results, with Joy at 24 and Anger at 21. Sadness had 13 intentions, while Fear and Nervousness had 5 and 4 purchase intentions, respectively.

3.2.4. EmotionPush

EmotionPush included over 10,900 Facebook messages, with 34 messages showing an intention to obtain a product or service. Neutral had the most instances, with 31 purchase intentions, while Joy was a distant second with 3. Other emotions like Anticipation, Tiredness, Anger, Fear, and Sadness had zero purchase intentions.

4. Results

4.1. Comparing Results in Four Datasets

Table 1 and Figure 1 illustrate the comparison of users' neutral and emotional states in our four datasets. In EmotionLines, six purchases occurred when users' emotions were neutral, while thirteen purchases occurred when users' emotions were non-neutral, which included Joyful, Mad, Powerful, and others. In the CARER dataset, 66 purchases took place in emotional states such as Joy, Sadness, Fear, Anger, and Surprise, with no records of neutral emotions. In the GoEmotion dataset, 251 purchases were associated with Neutral emotions, while 67 purchases occurred when users had non-neutral emotions, including Anger, Fear, Joy, Nervousness, and Sadness. Lastly, in EmotionPush, 31 purchases were recorded in a neutral emotional state, with only 3 emotional purchases. In EmotionPush, non-neutral emotions included Joy, Anticipation, Tiredness, Anger, Fear, and Sadness.

Table 2. 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

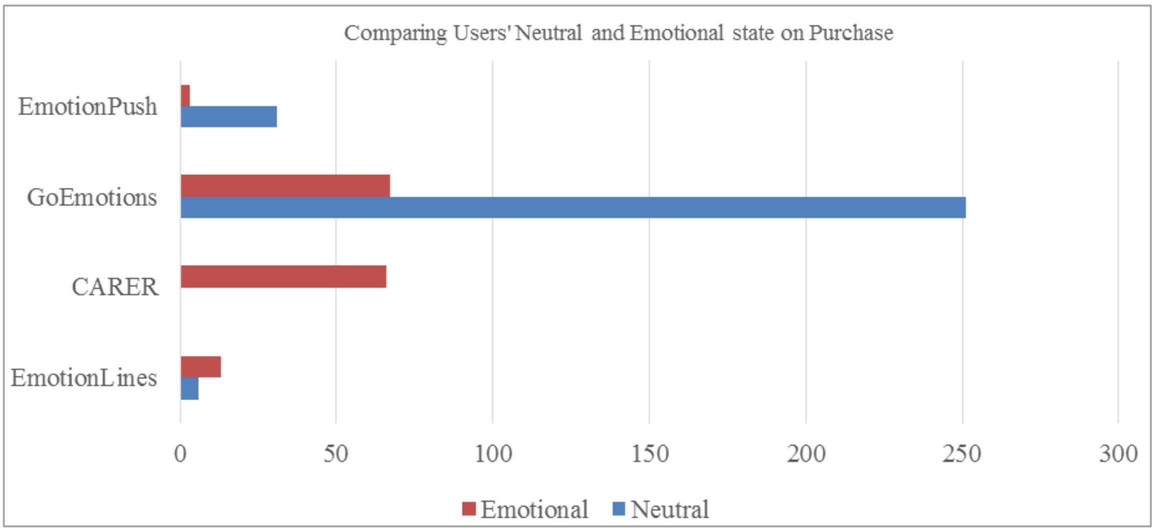

Figure 1. Comparing Users' Neutral and Emotional State on Purchase Intention.

4.2. Hypothesis Testing

4.2.1. EmotionLines

We rejected the alternative hypothesis since the dataset indicated that Neutral was among the top two emotions with an impact on purchase intention. While Joy ranked as the primary emotion influencing purchase intention, Neutral came in second, and Mad was third. Additionally, there were a total of six instances of neutral emotions, while there were thirteen instances of non-neutral emotions. Consequently, we could not accept the alternative hypothesis and had to reject it. Table 3 displays the percentage of purchase intentions in the EmotionLines dataset.

Table 3. 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 2 shows our result in a Pivot Chart.

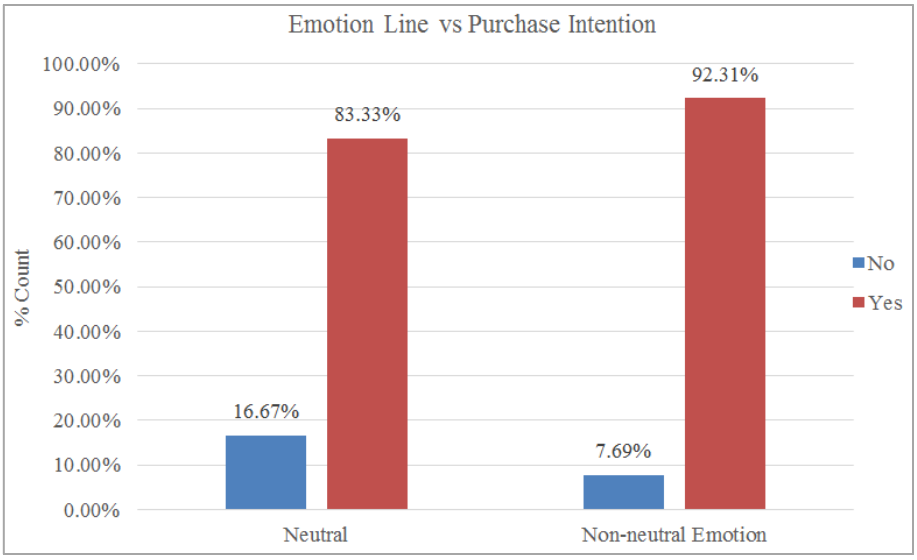

Figure 2. *EmotionLines vs Purchase Intention PivotChart.*

Table 4 illustrates the crosstabulation of Emotion and Purchase Intention in the EmotionLines dataset. It presents the distribution of purchase intentions among both Neutral and Non-neutral Emotions, represented as percentages.

Table 4. *EmotionLines & Purchase Intention Crosstabulation.*

Emotion * Purchase intention Crosstabulation					
			Purchase intention		**Total**
			No	**Yes**	
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 displays the results of the chi-square test conducted on the EmotionLines dataset. This table provides statistical information regarding the association between Emotion and Purchase Intention, assessing the significance of this relationship.

Table 5. *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		

Chi-Square Tests					
	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Fisher's Exact Test				1.000	.544
N of Valid Cases	19				

a. 2 cells (50.0%) have expected count less than 5. The minimum expected count is.63.
b. Computed only for a 2x2 table

The P-value (0.554) was greater than the level of significance (0.05). Consequently, we retained the null hypothesis and concluded that there was no relationship between emotion and purchase intention. In other words, emotion did not influence purchase intention.

4.2.2. Emotion Lines

We were unable to conduct the Chi-squared test on this dataset. The significant difference between this dataset and the other three was the absence of the Neutral label, which was replaced with "Others," resulting in zero instances in our results. However, Joy had 32 instances, and Sadness had 14. This dataset indicated 0 for Neutral emotions and 66 for Non-neutral emotions.

4.2.3. Go Emotion

We rejected the alternative hypothesis since the dataset revealed that Neutral was the dominant emotion influencing purchase intention, with a count of 251, compared to Joy with 24 and Anger with 21. Table 8 also displayed 251 instances of Neutral emotion and 67 instances of non-neutral emotion. This dataset highlighted that, after Neutral, Joy continued to play a significant role in purchase intention. This similarity was observed between this dataset and EmotionLines and CARER. Table 5 shows purchase intention by percentage of Go-Emotion.

Table 6. 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 3 shows our result in a Pivot Chart

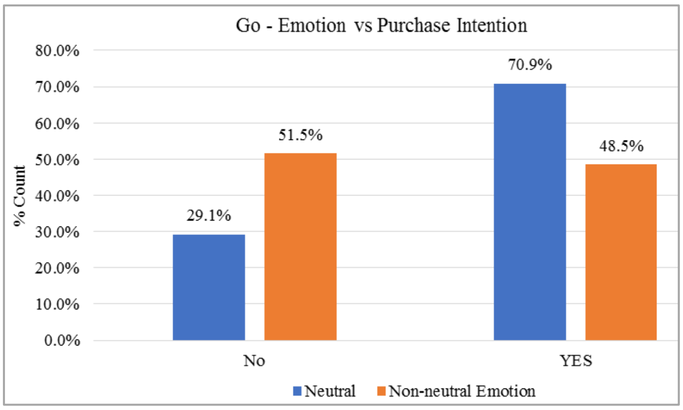

Figure 3. Go-Emotion vs Purchase Intention PivotChart.

Table 7 presents the crosstabulation analysis conducted on the GoEmotion dataset. This table showcases the interplay between Emotion and Purchase Intention within the dataset, displaying the distribution of purchase intentions among different emotional states.

Table 7. GoEmotion & Purchase Intention Crosstabulation.

Emotion * Purchase Intention Crosstabulation					
			Purchase Intention		Total
			No	Yes	
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 8 showcases the results of the chi-square tests performed on the GoEmotion dataset. This table provides statistical insights into the relationship between Emotion and Purchase Intention within the dataset, assessing the significance of this association.

Table 8. 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 less than 5. The minimum expected count is 11.40.
b. Computed only for a 2x2 table

The P-value (0.19) was greater than the level of significance (0.05). Therefore, we retained the null hypothesis and concluded that there was no relationship between emotion and purchase intention. In other words, emotion did not influence purchase intention.

4.2.4. Emotion Push

We rejected the alternative hypothesis for this dataset, which indicated that Neutral was the predominant emotion influencing purchase intention. Neutral had a count of 31, while the second emotion, Joy, had only 3 instances of purchase intention. All the other emotions combined showed zero purchase intentions. Table 8 provides a comparison between 31 instances of Neutral Emotions and 3 of Non-neutral emotions. This dataset also highlighted the significant role played by Joy in purchase intention. Table 9 shows purchase intention by the percentage of Emotion Push.

***Table 9**. EmotionPush 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 4 shows our result in a Pivot Chart

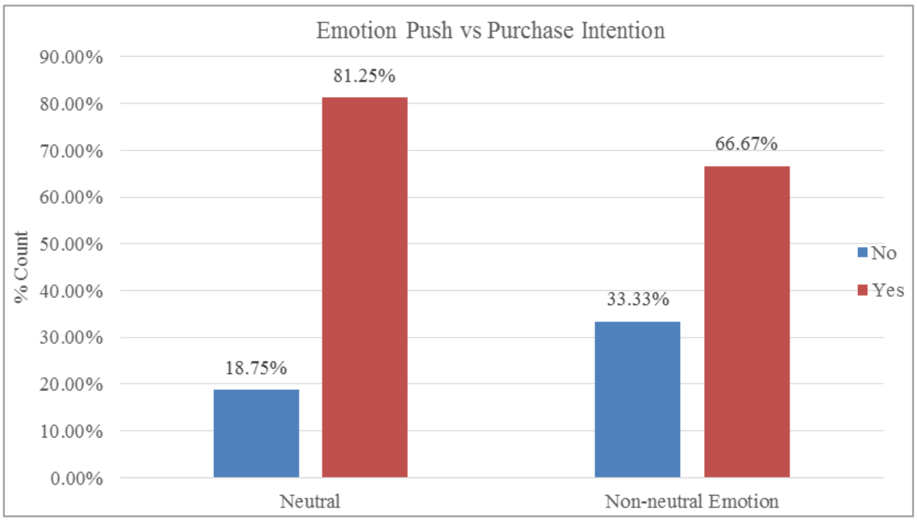

***Figure 4**. Emotion Push vs Purchase Intention Pivot Chart.*

Table 10 illustrates the crosstabulation analysis of Emotion and Purchase Intention in the EmotionPush dataset. This table reveals the distribution of purchase intentions across different emotional states, shedding light on the relationship between these variables.

***Table 10**. Purchase Intention & Emotion Crosstabulation.*

Purchase intention * Emotion Crosstabulation					
			Emotion		**Total**
			Neutral	**Non-neutral Emotion**	
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 11 presents the results of the chi-square tests conducted on the EmotionPush dataset. This table offers statistical insights into the relationship between Emotion and Purchase Intention within the dataset, assessing the significance of this relationship through statistical analysis.

Table 11. *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

The P-value (0.546) was greater than the level of significance (0.05). Consequently, we retained the null hypothesis and concluded that there was no relationship between emotion and purchase intention. In other words, emotion did not influence purchase intention.

When comparing all four datasets, it was evident that although Joy was not the primary emotion influencing purchase intention, it consistently played a significant role, particularly after the Neutral emotion. This observation aligned with our findings from the systematic literature review, which emphasized the impact of positive mood on purchase intention.

5. Conclusion

We had identified four datasets, each from entirely different sources (EmotionLines, CARER, GoEmotion, and EmotionPush). This diversity allowed us to test our hypothesis across a range of sources. We filtered the sentences and identified those indicating a purchase through observational methods, utilizing words with precise purchase-related meanings, as well as sentences with multiple interpretations that could imply a purchase.

The results of our hypothesis testing led to the rejection of our alternative hypothesis. The testing revealed that the Neutral emotion was the primary emotion associated with purchase intention. Additionally, Joy emerged as the second most influential emotion affecting purchase intention.

6. Limitations and Future Directions

We selected four datasets with characteristics resembling chatbot conversations to test our hypothesis. However, having access to actual chat histories of customers with a customer service chatbot would provide valuable insights into customer interactions with computers and their emotional dynamics. Since customer service often deals with complaints and technical queries, many detected emotions in the chats may include anger, frustration, or disappointment. Nonetheless, handling customer requests and successfully resolving their issues could potentially lead to changes in emotional states during the course of the conversation.

Conflicts of Interest

The authors declare no conflicts of interest.

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