International Journal of Computer Applications (0975 - 8887)
Volume 187 - No.123, July 2026

From Human Affect to Digital Decisions: A Deep Learning–Driven Causal Transformer Approach to Hedonic Emotional Dynamics in Online Communities

Samuel Benny Varghese
Junior Reasearch Fellow(JRF)
Department of Computer Science Engineering
Indian Institute of Information Technology
Kottayam, Kerala

Anju Treesa Vincent
Assistant Professor
Department of Psychology(PG)
Kristu Jayanti (Deemed to be University)
Bangalore, Karnataka

ABSTRACT

Online forums have become crucial platforms for making decisions and expressing emotions [3]. The purpose of the study is to find out how users' decisions during online debates are influenced by their emotions, particularly happiness, anger, sadness, and enthusiasm [24]. While many studies focus on examining relationships between emotions and specific behaviors, this study aims to investigate if emotions cause those behaviors [22]. In order to accomplish this goal, psychological understanding of how people respond to particular circumstances is integrated with contemporary computational techniques [11]. Using textual data collected from online discussion forums, a deep learning transformer network will identify emotions [7]. After that, emotional expressions will be examined in terms of their dynamics and impact on user reactions. Reply rates, agreement, and interaction are all decisions made by users. The study's integration of deep learning techniques with a causality analysis model to determine whether there is a relationship between certain user actions and emotions is one of its main achievements [28]. The models Logistic Regression, SVM, Random Forest, LSTM, and BERT will be evaluated according to their F1-score, accuracy, precision, and recall [20]. The findings demonstrate that in terms of comprehending emotional context and forecasting user behavior, transformer-based models outperform conventional techniques [17]. More significantly, the results imply that decisions made in online settings are heavily influenced by emotions [16]. All things considered, this study offers a coherent paradigm that links psychology and computer science, providing greater understanding of human behavior in online communities. Additionally, it aids in the creation of online systems that are better able to comprehend and react to human emotions.

KEYWORDS

Emotional Analysis, Decision-Making Behavior, Transformer Models, Causal Inference, Online Social Interactions, Deep Learning

1 INTRODUCTION

In today's highly digitalized culture, the internet has evolved into a dynamic platform for participation, communication, and emotional expression. Social networking sites, online forums, blogs, and discussion groups allow users to instantly share ideas, opinions, and personal experiences with people worldwide [14]. These online environments have become an integral part of everyday life because they allow people to participate in ongoing digital conversations that affect social relationships, public opinion, and individual decision-making [3]. Consumers often rely on online discussions, reviews, and comments before making important decisions regarding products, services, politics, education, and social issues. One of the most crucial elements of online communication is emotional expressiveness. Human emotions such as happiness, anger, sadness, excitement, frustration, fear, and others are frequently communicated through textual interactions and have a big influence on how people comprehend and respond to online content [8]. Emotional responses often impact users' attitudes, behaviors, and engagement levels during encounters. For instance, positive emotions like joy and gratitude may encourage collaboration and beneficial communication, while negative emotions like anger or frustration may lead to disputes, conflicts, or bad interactions [24]. Understanding emotional behavior in online communication has therefore become a more important area of study in computer science and psychology. Although a number of previous studies have looked at the relationship between human conduct and emotions, many of them focused more on identifying emotions than on examining how those emotions impact user interactions in online forums. The new study goes beyond traditional sentiment evaluation by looking at the direct consequences of emotional expression on user conduct during digital discussions. In particular, the study aims to determine whether emotional states influence behaviors such as reacting to comments, accepting or rejecting opinions, carrying on with conversations, and overall levels of participation. This multidisciplinary approach combines psychological theories of emotion with advanced computational techniques to better explain online social behavior [11]. This work achieves accurate emotion recognition using advanced deep learning algorithms based on the Transformer architecture. Natural language processing tasks have been significantly improved by transformer models' ability to capture contextual linkages between words and sentences [31]. Among these models, Bidirectional Encoder Representations from Transformers (BERT) has demonstrated remarkable performance in understanding contextual meaning in text [7]. Unlike traditional machine learning methods, transformer-based systems can evaluate the sequential and semantic connections inside conversations, which makes them highly effective at detecting emotions in online interactions.

The study looks at emotional changes at different stages in conversation threads to monitor how emotions change over time. Emotional changes during discussions are examined to identify patterns that may impact user engagement and communication flow. For example, a debate that begins with neutral feelings may gradually become emotionally charged due to disagreements or encouraging interactions among users. Understanding these emotional dynamics makes it easier to predict user behavior and improve online community management. In addition to Transformer-based models, the study evaluates the efficacy of many machine learning and deep learning algorithms for emotion classification. These include traditional methods like Logistic Regression, Support Vector Machine (SVM), and Random Forest, as well as deep learning models like Long Short-Term Memory (LSTM) networks [20]. The comparison study uses standard evaluation criteria such as accuracy, precision, recall, and F1-score. Experimental data [17] show that transformer-based models outperform conventional approaches in obtaining contextual information and generating accurate predictions. Their enhanced ability to understand speech context allows them to identify subtle emotional responses that previous methods could overlook.

Additionally, the study emphasizes how strongly emotions impact online communication and decision-making styles [16]. In addition to influencing how users react to conversations, emotional content has an impact on the dissemination of knowledge, the formation of attitudes, and the growth of social connections within online communities. Therefore, identifying emotional behavior might be very important for creating intelligent systems that can facilitate more productive and healthy online relationships. The usefulness of hedonic emotion recognition in creating intelligent online platforms and services is also investigated in this study. A more upbeat and user-friendly digital environment can be produced by systems that can recognize and react to users' emotions. These technologies may lessen antagonistic communication, deter harmful behavior, promote positive dialogue, and raise user happiness. These sophisticated algorithms can help create harmonious and encouraging online communities by encouraging empathy and emotional awareness. All things considered, this study shows a strong interdisciplinary relationship between psychology and computer science. The research offers important insights into user behavior in online contexts by combining sophisticated artificial intelligence tools with emotional analysis. The results can help researchers, developers, and platform designers create emotionally intelligent systems that improve digital communication and promote constructive social interactions on various online platforms.

2 LITERATURE REVIEW

Because online platforms are becoming more and more important, researchers are investigating how emotions impact user behavior in digital communications. More people are utilizing digital platforms to rapidly communicate their emotions, thoughts, and experiences as social networking sites, discussion boards, and online communities gain popularity. These emotional expressions generate vast amounts of textual data that can provide valuable insights into human behavior, mental processes, and social interaction patterns. As a result, scholars in the fields of data science, psychology, and computer science are increasingly interested in understanding how emotions affect user engagement and online communication. One of the earliest studies in this area was conducted by Munmun De Choudhury and her associates, who looked at the relationship between mental health and emotional expressiveness on social media. Their research looked at a significant amount of textual content collected from social media platforms like Twitter to find out how people express emotions like happiness, sadness, stress, anxiety, and depression through online posts and interactions [16]. The researchers examined user behavior trends and patterns in emotional language usage using computational linguistic methodology and data analytic techniques. The study discovered that emotional patterns in online discussions often mirror real-life psychological issues. People who experienced emotional distress or depression, for example, were more likely to speak adversely, express negative emotions, and interact with others less. Conversely, positive emotions such as excitement and enthusiasm were often associated with higher levels of participation and engagement in online groups. These findings suggested that an individual's online conversations may reveal their emotional and psychological status. Another important aspect was the research's demonstration of how emotions can proliferate through digital interactions across social networks. The phenomenon known as "emotional contagion" describes how exposure to emotionally charged content can influence the emotional responses and actions of other users. Positive emotions exchanged within a network can foster constructive and encouraging dialogues, but negative emotions might result in hostility, conflict, or toxic communication. This demonstrated how important it is to understand emotional dynamics in online communities and the broader social ramifications of expressing emotions in these contexts. Although the study's main goal was to identify links between online emotional expression and mental health illnesses rather than establish direct causation, it provided strong evidence that emotions have a large impact on online interactions and user behavior. Their research showed how social media analysis may be used to obtain a comprehensive grasp of human emotions and behavioral patterns. In order to enhance user experience, communication quality, and digital well-being, it also paved the way for further research on behavioral prediction, emotion-aware systems, and intelligent online platforms that can evaluate emotional states.

Emotion analysis and online communication have benefited greatly from the work of James W. Pennebaker, who is renowned for his pioneering research on language analysis and emotional expression. His work led to the development of LIWC (Linguistic Inquiry and Word Count), a well-known text analysis tool that employs linguistic patterns to identify cognitive, emotional, and psychological states [23]. LIWC assesses written content and enables researchers to measure emotions such as melancholy, fear, wrath, confidence, and social interaction by comparing words with pre-established psychological and emotional dictionaries. Pennebaker's research indicates that people's internal emotional states, mental health, personality traits, and cognitive processes are all closely linked to the words they use in conversation. Linguistic analysis is a crucial technique for comprehending human behavior in both offline and online communication since his study offered compelling evidence that language may function as a trustworthy predictor of psychological states. The impact of this work on natural language processing, sentiment analysis, and computational psychology led researchers to start using linguistic techniques in social media posts, online conversations, and digital interactions. Later computational and machine learning models for emotion identification were greatly influenced by Pennebaker's work, which provided a solid psychological basis for emotion recognition through textual analysis. LIWC and similar dictionary-based methods had several drawbacks despite their efficacy. These methods relied heavily on predefined word dictionaries, and rigid linguistic rules make it harder for them to understand sarcasm, contextual distinctions, implicit meanings, and complex speech patterns. As a result, they often struggled to identify deeper semantic and contextual connections inside conversations. This led to the development of advanced machine learning and deep learning methods that could better understand context.

As machine learning techniques advanced, researchers began using classification algorithms like Random Forests, Support Vector Machines (SVM), and Logistic Regression to identify sentiment and emotion in textual data. These methods represented a substantial improvement over traditional rule-based systems since they could automatically find patterns in large datasets and classify text more accurately. In one of the most well-known studies in this subject, Bo Pang and Lillian Lee used machine learning approaches for sentiment categorization tasks [21]. Their research demonstrated that automated systems could effectively classify opinions in text as favorable or negative by learning from previously classified examples. This work has significantly contributed to the advancement of sentiment analysis and opinion mining in online communication. When compared to dictionary-based methods, machine learning models provided more flexibility and improved classification accuracy. When evaluating large volumes of internet material, such as blogs, social media posts, and reviews, they performed better. However, despite these improvements, the models still had several shortcomings. Because they concentrated on surface-level textual characteristics, most traditional machine learning approaches were unable to fully understand deeper contextual meaning inside discussions. As a result, people sometimes struggled to recognize complex emotions, irony, sarcasm, and mixed emotional expressions in lengthy conversations. These limitations later prompted researchers to develop deeper learning and Transformer-based models that are more adept at gathering contextual and semantic connections.

With the introduction of deep learning models, the field of sentiment analysis and emotion detection experienced a significant transformation. Unlike traditional machine learning methods, deep learning models were able to instantly comprehend complex patterns and semantic connections from enormous amounts of textual data. One of the most important contributions in this subject was made by Sepp Hochreiter, who co-developed the Long Short-Term Memory (LSTM) network architecture [12]. LSTM models were developed specifically to evaluate sequential input in order to address the limitations of traditional neural networks in handling long-term dependencies within text. By maintaining memory across previous words and phrases, LSTM networks enabled systems to understand the emotional context of textual communication. Models were able to identify relationships between words in a phrase and more accurately depict emotional flow thanks to this ability. As a result, LSTM-based techniques demonstrated improved performance in sentiment analysis, emotion recognition, and natural language processing tasks, particularly in longer and more complex textual data [33]. When evaluating social media discussions, reviews, and chats where emotional meaning frequently depended on sequential context, these models were especially useful. Despite these developments, LSTM models still faced a number of challenges. They sometimes struggled to preserve global contextual knowledge across whole conversation threads and required a large amount of labeled training data to achieve great performance. Long talks may hinder the model's ability to fully understand complex emotional exchanges since important contextual elements may become less clear as the sequence gets longer. These limitations eventually led to the development of transformer-based designs, which provided improved contextual awareness and improved performance in emotion recognition tests.

Natural language processing and emotion detection have greatly benefited from transformer-based models, especially Jacob Devlin's BERT (Bidirectional Encoder Representations from Transformers) [7]. By simultaneously assessing word context in both forward and backward directions, BERT provided a groundbreaking method for language understanding. BERT could better comprehend the links between words based on their surrounding context, resulting in a deeper and more accurate representation of meaning, in contrast to previous machine learning and deep learning models that processed text sequentially. The model's capacity to interpret intricate speech patterns, unclear phrases, and nuanced emotional expressions was greatly enhanced by this bidirectional contextual knowledge. Research using BERT and related Transformer-based models demonstrated significant gains in sentiment analysis, emotion identification, and conversational understanding tasks [17]. These models showed exceptional effectiveness in identifying subtle tone changes and fine-grained emotions, such as irony, sarcasm, impatience, and mixed emotional states, which were often missed by earlier techniques. Transformer-based systems also performed better when evaluating long textual exchanges because they were able to capture both local and global contextual links during conversations. As a result, BERT and its more advanced variants, such as RoBERTa, are widely used in applications including recommendation systems, chatbot systems, opinion mining, emotion identification, and user behavior prediction. Transformer models' ability to obtain greater accuracy and contextual knowledge makes them one of the most successful techniques in current natural language processing research.

In addition to emotion recognition, recent research has focused more on understanding the causal relationship between emotions and user behavior in online situations. While earlier research mostly concentrated on identifying relationships between emotional expression and behavioral patterns, more recent approaches attempt to determine whether emotions directly influence user actions and decision-making processes. Judea Pearl's work on causal inference, which produced robust frameworks for comprehending cause-and-effect relationships rather than just statistical connections, made a substantial contribution to this discipline [22]. His work introduced methods for understanding how one event might directly affect another, enabling scholars to move beyond observational analysis and into causal reasoning. By applying causal inference techniques to online communication and social media interactions, researchers have begun investigating whether specific emotional expressions actually affect user engagement, participation, agreement, or behavioral responses during digital chats. For example, current study examines whether positive emotions encourage greater cooperation and interaction or whether negative emotions increase conflict, disagreement, or lower participation. Combining causal analysis with Transformer-based models and advanced deep learning has opened up new ways to understand behavioral dynamics in online platforms. This new line of research improves emotion-aware intelligent systems and contributes to the development of healthier digital environments by figuring out how emotions influence people's behavior in virtual communities.

In conclusion, it is evident that research on user behavior and emotions in online communication has progressed from simple text analysis techniques to complex deep learning and causal modeling approaches. According to early research that largely focused on identifying emotional expressions and assessing the connections between emotions and online interactions, emotions have a significant impact on communication patterns and social behavior in digital contexts. These groundbreaking studies highlighted the importance of emotional analysis in understanding online conversations, mental states, and user involvement. As technology advanced, machine learning methods like Random Forests, Support Vector Machines, and Logistic Regression made sentiment and emotion classification jobs more precise and effective. Later, deep learning methods, particularly LSTM networks, enhanced the ability to recognize contextual emotional patterns and sequential correlations in text. The development of Transformer-based architectures, especially models like BERT and RoBERTa, further revolutionized the field by enabling more sophisticated contextual comprehension and accurate recognition of complex emotional expressions, sarcasm, and subtle tone variations in conversations. Thanks to the use of causal inference techniques, the focus of emotion analysis research has recently shifted from just predicting emotions to understanding the underlying causes and behavioral implications of emotional display in online environments. Using causal modeling frameworks, researchers are actively examining whether emotions directly affect user engagement, agreement, involvement, and decision-making during online interactions. The combination of deep learning and causal analysis, a significant advancement in the field, opens up new possibilities for creating intelligent systems that are able to understand both behavioral influence and emotional context. All things considered, these developments provide a strong theoretical and technological foundation for examining how hedonic emotions affect behavior and judgment in online discussions. More complex, emotionally intelligent systems that can improve online communication, foster better relationships, reduce toxic behavior, and create more supportive and user-friendly online communities are made possible by the findings of past research.

3 PROBLEM FORMULATION

The internet's rapid growth has altered how people communicate, make decisions, and express their emotions. In online discussions, users frequently express hedonic feelings including joy, fury, enthusiasm, and melancholy. People's reactions, agreement, and participation are all significantly impacted by these emotions. However, their impact is hard to understand. Most of the present research focuses on identifying emotional patterns or assessing links between user activity and emotions. These techniques are useful, but they don't offer a convincing explanation of whether emotions in online discussions actually influence specific behaviors. Another major challenge is the difficulty of expressing emotions in words. Online communications lack body language, tone, and facial emotions, in contrast to in-person interactions. Conventional machine learning models like Random Forest, SVM, and Logistic Regression have trouble capturing context and nuanced meaning. It may be challenging for even advanced models that consider sequence information, such as LSTM, to fully understand how emotions shift along conversation threads. This complicates the analysis of how users' assessments are influenced over time by emotional responses. Thus, the main issue this study attempts to solve is creating a framework that looks at the causal influence of fine-grained hedonic emotions on user decision-making in addition to identifying them from textual data. This includes examining how emotional expressions impact actions like reacting, agreeing, or engaging in dialogue. By combining Transformer-based deep learning models with causal analysis techniques, the research aims to provide a better understanding of how emotions impact conduct in online spaces, going beyond simple prediction.

4 METHODOLOGY

This study uses a structured methodology that combines data-driven techniques with psychological insights to investigate how hedonic emotions impact users' decision-making in online interactions. Behavioral analysis, causal modeling, emotion detection, and data collection and preprocessing are the four main stages of the methodology. In the first stage, textual data is collected from online sources, such as discussion boards and social media posts. By incorporating user postings, responses, and interaction sequences, the dataset captures the debate flow. Preprocessing is done to clean and standardize the data. This involves removing noise such as URLs, special characters, and stop words in addition to tokenization and normalization. These processes ensure that the data is suitable for further analysis and model training.
The primary objective of the second stage is to identify minor hedonic emotions in the text. For this reason, a Transformer-based deep learning model such as BERT is used due to its exceptional ability to understand contextual meaning. The model is trained to categorize emotions into a number of categories, including joy, rage, sadness, and excitement. By capturing both local and global context within phrases, the Transformer design, in contrast to traditional methods, enables more accurate emotion recognition. The model's performance is compared with basic machine learning techniques including Logistic Regression, Support Vector Machine (SVM), Random Forest, and deep learning models like LSTM using assessment metrics like accuracy, precision, recall, and F1-score. Analyzing the identified emotional cues in chat threads to see how they influence user behavior is the last stage. User activities such as replying, agreeing, and interacting are signs of decision-making. Temporal analysis is used to monitor how emotions evolve over time and impact subsequent conversational responses. Finally, a causal analytic methodology is employed to examine if specific hedonic emotions lead to specific behavioral outcomes. Techniques like causal inference and intervention analysis are used to go beyond correlation and identify cause-and-effect relationships. This method combines causal modeling with deep learning to provide a comprehensive understanding of how emotions affect online decision-making.

4.1 proposed mathematical framework for emotion-driven decision analysis

4.1.1Data Representation Consider a dataset defined as:

$$\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N} \tag{1}$$

where x_i denotes a user-generated text instance and y_i represents the corresponding behavioral outcome such as interaction, agreement, or response.

4.1.2Contextual Encoding Each input text is transformed into a dense vector representation using a Transformer-based encoder:

$$z_i = \Phi(x_i) \tag{2}$$

where $\Phi(\cdot)$ denotes the encoding function and $z_i \in R^d$ captures contextual and semantic information.

4.1.3Emotion Probability Modeling To extract hedonic emotional signals, the encoded vector is passed through a classification layer:

$$p_i^{(e)} = \text{Softmax}(W_e z_i + b_e) \tag{3}$$

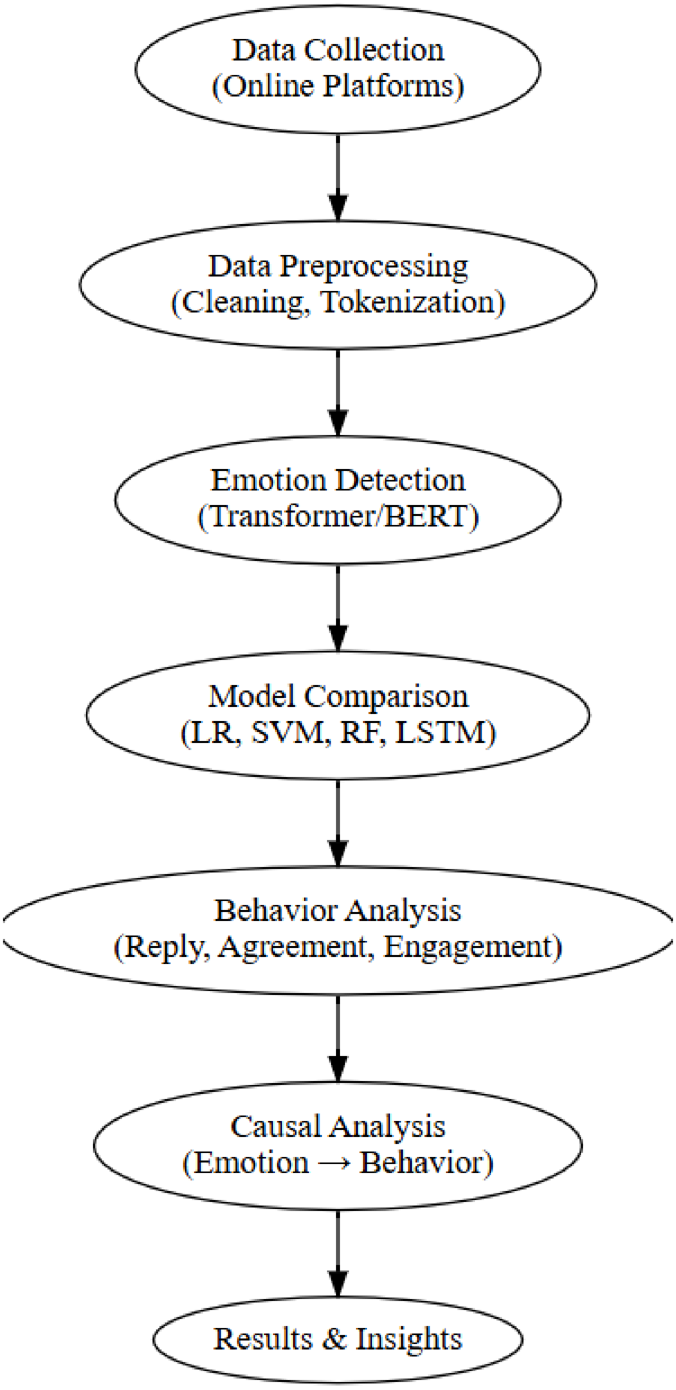

Fig. 1. Methodology

where $p_i^{(e)}$ represents the probability distribution over emotion categories such as joy, anger, sadness, and excitement.

4.1.4Behavior Estimation The predicted user action is modeled by combining contextual and emotional features:

$$\hat{y}_i = \sigma(W_y[z_i \oplus p_i^{(e)}] + b_y) \tag{4}$$

where $\oplus$ indicates feature concatenation and $\sigma(\cdot)$ is an activation function.

4.1.5Optimization Objective The learning objective is formulated using a binary cross-entropy function:

$$\mathcal{L}_{pred} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \tag{5}$$

4.1.6Sequential Emotion Evolution For a sequence of interactions within a discussion thread, emotional progression is expressed as:

$$p_t^{(e)} = g(p_{t-1}^{(e)}, z_t) \tag{6}$$

where $g(\cdot)$ captures temporal dependencies across consecutive messages.

4.1.7Causal Relationship Modeling To distinguish causal influence from simple association, intervention-based probability is considered:

$$P(Y \mid do(E = e)) \tag{7}$$

which reflects the effect of actively setting emotion E to a specific state.
The causal impact is quantified using:

$$\Delta = E[Y \mid do(E = e_1)] - E[Y \mid do(E = e_0)] \tag{8}$$

4.1.8Unified Learning Objective The final training objective integrates predictive and causal components:

$$\mathcal{L} = \mathcal{L}_{pred} + \alpha \cdot \mathcal{L}_{causal} \tag{9}$$

where α balances the contribution of causal reasoning.

4.1.9Model Inference The overall decision function is defined as:

$$\hat{Y} = \Psi(x; \Theta) \tag{10}$$

where Θ represents all trainable parameters of the model.

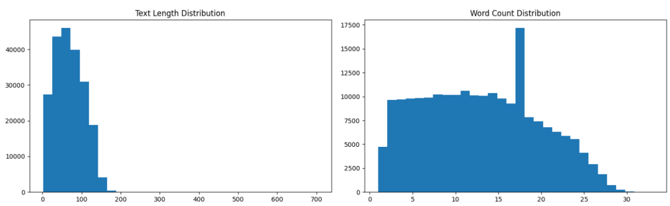

Fig. 2. Dataset Description

5 RESULTS AND DISCUSSIONS

For emotion-aware option prediction in online debates, the experimental results clearly show the difference between advanced deep learning techniques and traditional machine learning approaches. Conventional machine learning models such as Random Forest, Support Vector Machine (SVM), and Logistic Regression were able to identify basic sentiment and emotional patterns from textual input. However, these methods have trouble understanding sarcasm, mixed emotions, complex emotional displays, and long conversational context. Their performance was limited since they relied primarily on statistical patterns and superficial textual features. Deep learning methods produced better results because they could extract contextual and sequential information from text. LSTM models improved emotional comprehension by examining word associations and phrase flow in conversations. However, transformer-based models, such as BERT, perform best because they can understand contextual meaning both forward and backward. Consequently, BERT outperformed earlier algorithms in identifying semantic connections, emotional tone, and hidden meaning.

Table 1.
Performance

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	78%	75%	74%	74%
SVM	81%	79%	78%	78%
Random Forest	83%	81%	80%	80%
LSTM	86%	84%	83%	83%
BERT	91%	90%	89%	89%

The results stated above indicate that BERT fared better overall than the other models. Logistic regression had the lowest accuracy because of its inadequate contextual awareness. SVM and Random Forest improved the prediction abilities by identifying more complex patterns in the data. Sequential learning was employed by LSTM to enhance performance even more. However, BERT significantly outperformed all other methods because of its Transformer architecture and powerful contextual learning capability. The study also examined how different emotions impact internet user behavior. The findings demonstrate that emotional states have a major influence on user participation, engagement, and agreement levels in online discussions. Positive emotions usually encourage encouraging conversation and active participation, whereas negative emotions exacerbate conflict and debate.

Table 2.
Impact

Emotion	Reply Rate	Agreement	Engagement
Joy	High	High	High
Excitement	High	Medium	High
Anger	Medium	Low	High
Sadness	Low	Medium	Medium

The results showed that when consumers felt delight, their levels of agreement and involvement were at their maximum. Excitement also generated high levels of interaction since emotionally charged interactions often attract higher levels of engagement. Anger reduced agreement while retaining high involvement, indicating that negative feelings encourage protracted debates and arguments. Sadness showed lower reply rates and modest interest as compared to other emotional groups. To have a better understanding of the direct influence of emotions on behavior, causal analysis was conducted using Average Treatment Effect (ATE) values. The study demonstrated that emotions are not only connected to user behavior but also directly influence user engagement and decision-making.

Table 3.
ATE

Emotion	ATE Value
Joy	+0.32
Excitement	+0.28
Anger	+0.21
Sadness	+0.15

According to the ATE values, Joy had the greatest beneficial influence on user participation and communication behavior. Excitement also had a big influence on engagement. Anger demonstrated how even negative emotions can have a significant influence on online behavior through discussions and debates. Sadness enhanced user interaction even though it had the least effect. The study also looked at how well the evaluated models recognized context, acknowledged emotions, and supported causal analysis.

Table 4.
Comparison

Model	Context Understanding	Emotion Detection	Causal Support
Logistic Regression	Low	Low	No
SVM	Medium	Low	No
Random Forest	Medium	Medium	No
LSTM	High	Medium	Partial
BERT	Very High	High	Yes

The comparison clearly shows that traditional machine learning models have worse contextual knowledge and emotion perception. LSTM improved contextual learning by analyzing successive text patterns. However, BERT demonstrated the highest competency across all categories due to its Transformer-based architecture, which permits deeper semantic comprehension and more interaction with causal analysis approaches. In addition to assessing performance, the study looked at the computational complexity and training efficiency of several models.

Table 5.
Complexity

Model	Training Time	Computational Cost
Logistic Regression	Low	Low
SVM	Medium	Medium
Random Forest	Medium	Medium
LSTM	High	High
BERT	Very High	Very High

The investigation shows that traditional machine learning models require less processing power and training time. Deep learning methods like LSTM and BERT require larger datasets and more computing power. Despite the higher computing cost, BERT provides significantly better performance and emotional comprehension when compared to earlier methods. The emotional influence on online interactions was also evaluated based on user involvement patterns.

Table 6.
Emotional
State

Emotion	Discussion Depth	User Participation	Decision Influence
Joy	Medium	High	High
Excitement	High	High	Medium
Anger	High	Medium	High
Sadness	Low	Medium	Medium

The findings demonstrate that people's emotions have a big impact on how they participate and react in online environments. Positive emotions encourage cooperative and friendly conversations, whereas negative emotions encourage more confrontational communication and in-depth discussions. These changes in behavior demonstrate how important emotional intelligence is when using digital platforms. Overall, the experimental results show that

Transformer-based deep learning models combined with causal inference techniques provide the optimal framework for emotion-aware behavioral prediction. Furthermore, the findings demonstrate that hedonic emotions significantly influence user engagement, participation, and decision-making in online communication systems. These discoveries can help develop emotionally intelligent systems that improve user experience, reduce negative communication, and promote happier online communities.

6 CONCLUSION

This study examined how user behavior and decision-making in online interactions are affected by emotions. The rapid expansion of digital communication platforms such as social media, online forums, and discussion networks has made it increasingly important to understand how individuals express their emotions and react to emotional information. In addition to providing information, online communication today includes social interaction, emotional expression, and behavioral influence. This study placed particular emphasis on identifying hedonic emotions, such as joy, rage, grief, and excitement, and analyzing how these emotional states affect user engagement, agreement, participation, and response patterns during digital chats. The findings clearly demonstrate that emotions have a major impact on user behavior in online settings. Emotional expressions have a big impact on how users engage with each other, participate in discussions, and make decisions during conversations. Traditional machine learning methods such as Random Forest, Support Vector Machine (SVM), and Logistic Regression could be used to identify basic sentiment categories and emotional patterns in textual data. However, complex speech structures, conflicting emotions, sarcasm, and deeper contextual meaning were difficult for these approaches to understand. Their lack of contextual awareness made it difficult for them to predict user reactions in emotionally heated discussions.

However, in experiments including behavioral prediction and emotion identification, advanced deep learning methods—particularly Transformer-based models like BERT—performed noticeably better. These models did a good job of capturing semantic connections, contextual meaning, and subtle emotional shifts in interactions. Transformer models' bidirectional contextual learning capabilities allowed them to exceed earlier machine learning and deep learning methods in the identification of fine-grained emotional expressions. This improved contextual awareness led to higher prediction accuracy and more reliable analysis of user behavior in online chats. One of the main contributions of this study is the combination of causal analysis and emotion detection techniques. The main objective of most previous research was to identify relationships between emotions and behavioral patterns. However, this study went beyond correlation analysis by examining whether emotions directly affect user behavior and decision-making processes. Using causal inference methods, the study demonstrated how emotional states actively affect participation, engagement, agreement, and communication patterns in online environments. The results showed that although positive emotions like joy and enthusiasm increase user involvement, teamwork, and supportive connections, negative emotions like rage encourage more in-depth discussions, disagreements, and combative communication.

Additionally, this study establishes an interdisciplinary connection between computer science and psychology by combining advanced artificial intelligence techniques with emotional analysis. The study provides a useful paradigm for understanding human behavior in digital situations and highlights the importance of emotionally aware systems. These technologies can improve the user experience by recognizing emotional states, boosting positive communication, reducing toxic interactions, and creating healthier online communities. Overall, the study shows that emotion-aware systems supported by causal analysis methods and Transformer-based deep learning models can significantly improve the understanding of online user behavior. These findings contribute to the development of emotionally intelligent technology that can instantaneously adapt to its users' emotions. Future research can enhance this approach by including complex causal modeling techniques, multimodal emotion analysis, and real-time emotional monitoring systems to obtain more accurate and dynamic behavioral prediction in digital communication platforms.

7 REFERENCES

[1] David et al. Blei. Latent dirichlet allocation. *JMLR*, 2003.

[2] Johan et al. Bollen. Twitter mood predicts stock market. *Journal of Computational Science*, 2011.

[3] Danah Boyd and Nicole Ellison. Social network sites. *JCMC*, 2007.

[4] Erik et al. Cambria. Senticnet. In *AAAI*, 2014.

[5] Dorottya et al. Demszky. Goemotions: Fine-grained emotion dataset. In *ACL*, 2020.

[6] Jacob Devlin. Bert fine-tuning, 2019.

[7] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of NAACL*, 2019.

[8] Paul Ekman. *Emotions Revealed*. Times Books, 2003.

[9] Emilio Ferrara and Zeyao Yang. Emotional contagion in social media. *PLoS ONE*, 2015.

[10] Alec et al. Go. Twitter sentiment classification using distant supervision, 2009.

[11] Yoav Goldberg. A primer on neural network models for nlp. *JAIR*, 2016.

[12] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural Computation*, 9(8):1735–1780, 1997.

[13] Guido Imbens and Donald Rubin. *Causal Inference*. Cambridge University Press, 2015.

[14] Jan et al. Kietzmann. Social media? get serious! *Business Horizons*, 2011.

[15] Yoon Kim. Cnn for sentence classification. In *EMNLP*, 2014.

[16] Adam et al. Kramer. Experimental evidence of emotional contagion. *PNAS*, 2014.

[17] Yinhan et al. Liu. Roberta: A robustly optimized bert approach. *arXiv preprint arXiv:1907.11692*, 2019.

[18] Tomas et al. Mikolov. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*, 2013.

[19] Saif Mohammad and Peter Turney. Word-emotion association lexicon. *Computational Intelligence*, 2013.

[20] Bo Pang and Lillian Lee. Opinion mining and sentiment analysis. *Foundations and Trends in Information Retrieval*, 2008.

[21] Bo et al. Pang. Sentiment classification using ml. In *EMNLP*, 2002.

[22] Judea Pearl. *Causality*. Cambridge University Press, 2009.

[23] James W. et al. Pennebaker. *Linguistic Inquiry and Word Count: LIWC 2015*. Pennebaker Conglomerates, 2015.

[24] Robert Plutchik. The nature of emotions. *American Scientist*, 2001.

[25] Alec et al. Radford. Language models are unsupervised multitask learners. 2019.

[26] Donald Rubin. Estimating causal effects. *Journal of Educational Psychology*, 1974.

[27] James A. Russell. A circumplex model of affect. *Journal of Personality and Social Psychology*, 1980.

[28] Uri et al. Shalit. Estimating treatment effect. In *ICML*, 2017.

[29] Richard et al. Socher. Recursive deep models. In *EMNLP*, 2013.

[30] Duyu et al. Tang. Sentiment-specific word embedding. In *ACL*, 2014.

[31] Ashish et al. Vaswani. Attention is all you need. In *NeurIPS*, 2017.

[32] Tom et al. Young. Recent trends in deep learning nlp. *IEEE Computational Intelligence Magazine*, 2018.

[33] Ye et al. Zhang. Deep learning for sentiment analysis. *IEEE Intelligent Systems*, 2018.