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An Interdisciplinary Review On Negative Emotions: Impact On Learning, Self-Regulation, And Professional Conduct

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Abstract: Positive and negative emotions both have a significant impact on how people think, act, and feel in general. The impact of negative emotions is examined in this review in a number of areas, such as emotion recognition, self-control, learning, mental health, academic dishonesty, and workplace behavior. This study examines research that was done between 2015 to 2024 using a variety of approaches, including fMRI, EEG, ECG, self-report measurements, and machine learning techniques. As instruments for classifying and analyzing emotional states, the Emotion Wheel and Emotion Analysis Framework are presented, improving the precision and comprehensibility of emotion identification systems.Datasets such as AMIGOS, DREAMER, and DEAP help make these models more applicable and dependable. Important discoveries show that unpleasant emotions can disrupt mental health and quality of life, undermine self-control, and have an impact on learning and academic achievement. However, resilience, social support, and exercise intensity are some of the elements that mitigate the negative emotional impact. The evaluation also emphasizes how servant leadership can lessen negative feelings among staff members and increase their capacity for innovative crisis adaptation. These findings' ramifications are examined in relation to workplace analysis, educational settings, mental health evaluation, and affective computing. Future studies should investigate multimodal strategies to enhance emotion recognition systems' precision and applicability.

Index Terms: Positive emotions, Negative emotions, Emotion recognition, EEG signals, Affective computing, Machine learning, Emotion Wheel.

I. Introduction

Emotions are essential to the human experience and have a big impact on behavior, thought processes, and general health. Positive and negative categories are frequently used to categorize these affective states, each of which has unique physiological and psychological functions. Joy and contentment are examples of positive emotions that improve psychological resilience, strengthen social ties, and improve mental agility. On the other hand, negative emotions like fear and anger serve as adaptive strategies that help people deal with obstacles and possible dangers. Even though they are often linked to discomfort, negative emotions are essential for motivation, self-preservation, and learning.

Affective computing, psychology, and neuroscience are just a few of the scientific fields that heavily rely on the distinction between positive and negative emotions. Positive emotions are associated with increased alpha wave activity and activation in the left prefrontal cortex, which is a sign of calm and wellbeing, according to electroencephalographic research. In contrast, negative emotions are associated with higher levels of theta and beta waves, primarily in the right prefrontal cortex, which is indicative of increased cognitive demands and stress. Researchers can objectively classify emotions through the analysis of these brain patterns, which promotes the development of emotion identification technology.

Emotion detection systems based on artificial intelligence, improving human-computer interactions, and mental health evaluation are all significantly impacted by the ability to accurately identify positive and negative emotions. EEG-based emotion classification offers a data-driven method for comprehending affective states, with potential uses in therapeutic interventions and real-time monitoring.

Emotion Wheel:

The Emotion Wheel is a hierarchical framework that facilitates structured emotional analysis by classifying emotions into three tiers: primary, secondary, and tertiary. Six fundamental emotions—Happiness, Sadness, Anger, Fear, Disgust, and Surprise—that serve as fundamental affective states form the basis of the approach. A thorough depiction of emotional events is provided by the expansion of these core emotions into secondary emotions, which in turn split into tertiary emotions. The systematic mapping of human emotional responses for research and computational modeling is made easier by this well-organized classification system.

The Emotion Wheel is a reference manual for classifying emotional states in the field of affective computing, namely in EEG-based emotion detection systems. The wheel's hierarchical structure can be used to correlate different affective states with variations in EEG signals across the different frequency bands (alpha, beta, theta, delta, and gamma). For example, higher levels of tension and alertness, which are associated with feelings of anger or fear, are linked to greater beta activity in the frontal lobe. On the other hand, alpha waves that are more prevalent are linked to calmer states and are frequently linked to feelings that fall under the Happiness category. The accuracy of machine learning models created for emotion categorization is improved by this structured labeling technique.

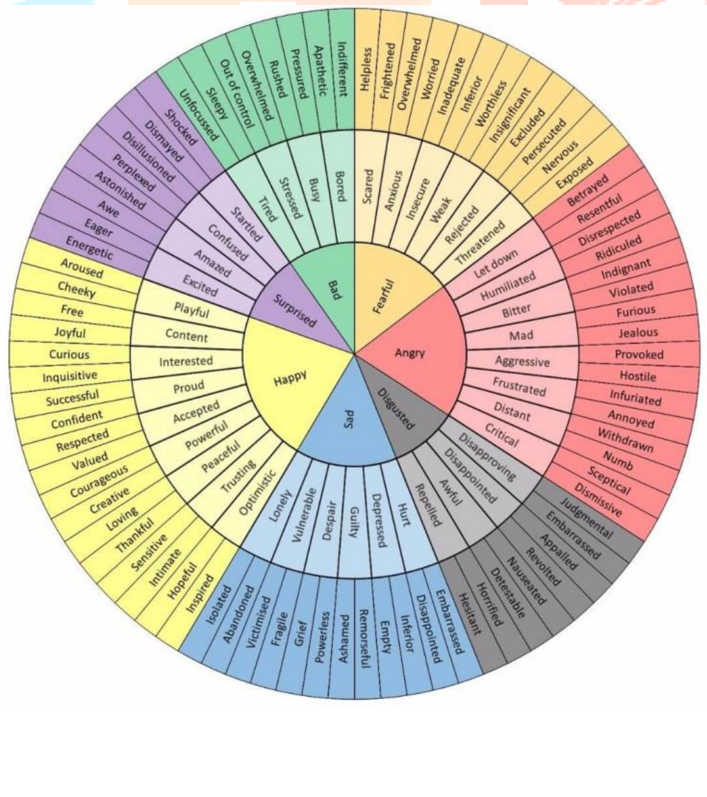

Figure 1: Emotion Wheel

The Emotion Wheel provides a systematic method for annotating emotions, which makes it especially useful in sentiment analysis, human-computer interaction, and psychological research. It can guide the structure of datasets for supervised learning models in deep learning applications, guaranteeing consistent representation of emotions. Moreover, this hierarchy can be used for cross-modal validation in multimodal emotion identification systems that combine EEG with textual or facial expression analysis. In order to improve the interpretability and dependability of affective computing models, researchers can correlate EEG signal patterns with distinct emotional categories.

Positive and negative emotions can be divided into two main categories. The experiences that are commonly referred to be "negative" are usually described as unpleasant and can potentially affect a person's everyday functioning and psychological health.

These three elements—collectively known as the components of emotion—are subjective experiences, cognitive evaluation, and physiological arousal. A person's upbringing, experiences, and cultural influences shape these factors, which cause differences in how they feel about similar circumstances. A number of ideas have been proposed over time to explain how these elements interact.[1]

II. Scope of the Review Research:

This review includes research on negative emotions from 2015 to 2024 in a number of areas, such as learning, mental health, academic dishonesty, emotion awareness, self-control, and workplace behavior. Finding out how negative emotions affect cognitive and behavioral results, as well as the underlying brain mechanisms underpinning them, is the main goal of the research. The methods used include self-report measurements, fMRI, EEG, ECG, and machine learning algorithms for emotion identification.

III. Emotion Analysis Framework

An Emotion Analysis Framework that describes a systematic procedure for recognizing and analyzing human emotions is depicted in the figure 2.

The five main components of this framework are data collection methods, preprocessing procedures, emotion categorization algorithms, analysis and interpretation strategies, and possible applications. Together, these elements gather emotional data, process it, classify feelings, analyze outcomes, and apply conclusions in real-world scenarios. Numerous disciplines, including affective computing, mental health research, educational studies, and workplace behavior analysis, make substantial use of this approach.

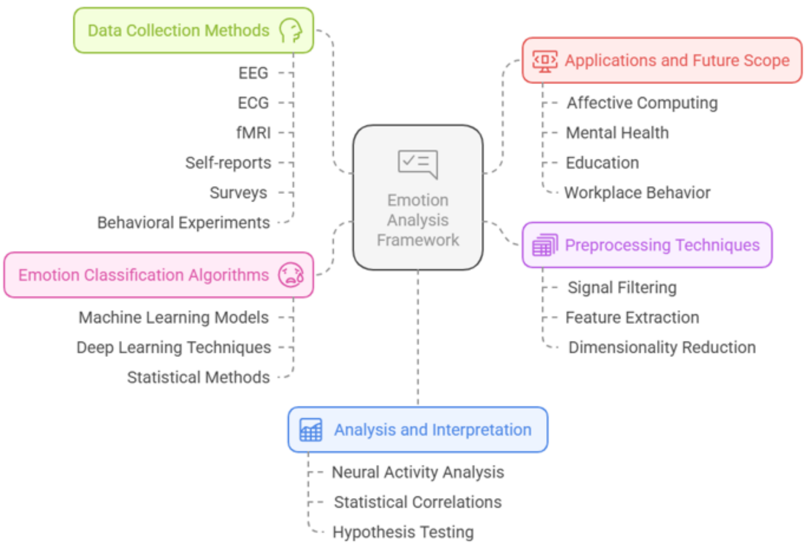

Figure 2: Emotion Analysis Framework

The foundation of emotion analysis is data collecting methods, which use a variety of approaches to capture emotional information. To identify emotional reactions, physiological sensors such as EEG, ECG, and fMRI monitor heart and brain activity. Furthermore, behavioral studies, questionnaires, and self-reports offer observational and subjective data that enables researchers to correlate stated emotions with physiological signals. Combining these techniques guarantees a complete dataset for additional study.

Following data collection, preprocessing methods improve accuracy and lower noise, preparing the data for analysis. This step entails lowering dimensionality to make complex datasets simpler, extracting features to find important emotional indicators, and filtering signals to eliminate unwanted interference. More accurate emotion classification results from these procedures, which guarantee that the input data is clean and controllable.

The ability to identify and classify emotions depends on emotion categorization algorithms. Automated emotion recognition is made possible by machine learning models like SVM and Random Forest as well as deep learning methods like CNN and RNN. Regression analysis and clustering are two statistical techniques that improve classification model accuracy. Emotional states can be accurately predicted using these methods.

Researchers can gain valuable insights by analyzing and interpreting classified emotions. The findings are validated by methods like hypothesis testing, statistical correlations, and brain activity analysis. Affective computing, mental health therapy, individualized education, and workplace behavior monitoring are just a few of the many uses for the results. Emotion analysis will continue to impact healthcare, emotional intelligence systems, and human-computer interaction as this field of study develops.

To improve affective computing, mental health, education, and workplace behavior, the Emotion Analysis Framework integrates data collection, preprocessing, categorization, and interpretation. This advances the development of applications for emotional intelligence and human-computer interaction.

Datasets used :

Figure 3: Datasets

a) DEAP Dataset: This extensively used dataset contains physiological signals for the identification of affect.
b) DREAMER Dataset: EEG and ECG signals for controlled emotion recognition.
b) AMIGOS Dataset: A multimodal dataset that encompasses group dynamics, personality traits, and affective reactions.
d) CUMULATE Dataset: This multimodal dataset examines how recognition accuracy changes as the number of negative emotion categories increases by merging EEG and ECG signals.
e) Dataset from Self-Report Surveys: A lot of research uses validated psychological measures like the Children's Hope Scale, the Positive and Negative Affect Schedule (PANAS), and Resilience Scales.

IV. REVIEW OF LITERATURE

Babiker, Areej et. al. (2015), studied negative emotions frequently lead to self-control failures, and one personality feature linked to these errors is negative urgency. While other hypotheses have suggested that a lack of prefrontal inhibitory responses is the main cause, this study explores a different theory: unpleasant emotions may overpower prefrontal cortex inhibitory areas, leading to a loss of self-control. Brain activity in those with strong negative urgency and control subjects during an emotional Go/No-Go test was investigated using fMRI.The results showed that those with high negative urgency activated more inhibitory brain areas than controls under negative emotional stimuli (but not positive or neutral ones), indicating a compensation strategy. Furthermore, greater rates of substance misuse at one-month and one-year follow-ups were predicted by increased anterior insula activity during negatively valenced inhibitory trials. These findings provide fresh insights into affect-driven impulsivity by indicating that self-control failure in people who are prone to negative urgency is caused by excessive activation of regulatory brain regions rather than by a lack of inhibition.[2]

Chester, David S. et. al. (2016), observed negative emotions frequently lead to self-control failures, and one personality feature linked to these errors is negative urgency. While other hypotheses have suggested that a lack of prefrontal inhibitory responses is the main cause, this study explores a different theory: unpleasant emotions may overpower prefrontal cortex inhibitory areas, leading to a loss of self-control. An fMRI study was carried out to look at the brain activity of control volunteers and people with strong negative urgency during an emotional Go/No-Go test. The results showed that those with high negative urgency activated more inhibitory brain areas than controls under negative emotional stimuli (but not positive or neutral ones), indicating a compensation strategy. Furthermore, greater rates of substance misuse at one-month and one-year follow-ups were predicted by increased anterior insula activity during negatively valenced inhibitory trials. These findings provide fresh insights into affect-driven impulsivity by indicating that self-control failure in people who are prone to negative urgency is caused by excessive activation of regulatory brain regions rather than by a lack of inhibition.[3]

Wallis, Chloe U. et. al. (2017), studied uncontrolled negative emotions, such as anxiety and depression, have been associated with reduced heart-rate variability (HRV) and increased cardiovascular death rates. A direct causal relationship between these disorders and dysfunction in ventromedial prefrontal cortex (vmPFC) areas 25 and 32 has not been proven. Furthermore, cross-species comparisons are made more difficult by differences between human neuroimaging studies and rodent fear extinction studies. Because marmoset monkeys and humans have more vmPFC similarities than rodents, this study uses them to investigate the brain-body interactions associated with negative emotional dysregulation. According to the results, regions 25 and 32 play different roles in controlling behavioral and cardiovascular reactions to unpleasant emotions. While improving resting heart rate variability, chemically deactivating region 25 reduced behavioral and autonomic responses to unpleasant emotions. Deactivating region 32, on the other hand, caused anxiety-related behavioral generalization. These findings provide fresh understanding of the neurological processes behind emotional disorders and cast doubt on established rodent-primate models.[4]

Rowe, Anna D. et. al. (2018), revealed that the importance of emotions in adult education and academic performance has been the subject of more recent study, which has moved beyond the conventional focus on test anxiety to include a broader range of unpleasant emotions. This qualitative study investigates how negative emotions appear and why they occur in academic settings. Researchers examined the emotional responses to several educational contexts by interviewing 36 staff members and students at an Australian university. Four main negative emotion categories—anger, sadness, fear, and boredom—were found to be most pertinent to learning using a prototype method to emotion studies. Additionally, compared to staff members, students reported feeling self-conscious feelings including guilt, embarrassment, and shame more frequently.Negative emotions were acknowledged as possibly helpful in certain situations, even though they were frequently seen as obstacles to motivation, performance, and learning. These findings highlight how crucial it is to embrace a social functional viewpoint in order to fully understand the complex roles that negative emotions play in learning and academic achievement.[5]

Vaccarezza, Maria Silvia. et. al. (2019), investigates the educational relevance of negative emotions associated with exemplarity (NEREs). We start by advocating for the crucial role of negative emotions in general, emphasizing their practical and inherent worth in achieving a meaningful existence. The analysis then concentrates on NEREs, assessing their ethical and educational significance through the perspective of previously established arguments. Subsequently, we introduce three educational strategies designed to amplify the positive moral influence of NEREs. The study concludes by proposing that character education rooted in exemplarism could be substantially improved through a more sophisticated grasp of the emotions involved in learning processes and a wider consideration of which emotions are deemed beneficial for educational objectives..[6]

According to Geng, Yaoguo et. al. (2020) teenagers' quality of life (QoL) in a community context is examined in relation to negative emotional states, such as stress, anxiety, and depression. The research focuses on the ways in which social support moderates this relationship and resilience mediates it. 6,401 teenagers between the ages of 9 and 15 were assessed by researchers using validated metrics for resilience, social support, negative emotions, and quality of life. Resilience was found to be a mediating component in the inverse connection between negative emotions and QoL. Additionally, social support was shown to buffer all pathways, increasing the beneficial effects of resilience on QoL while reducing the detrimental effects of emotional distress.These findings suggest that, despite feeling bad, teenagers who have larger social support systems had higher quality of life. The study emphasizes how crucial it is to build social support networks and resilience in order to lessen the psychological effects of unpleasant emotions. For creating treatments meant to improve the well-being of adolescents, it offers both theoretical understanding and real-world applications.[7]

Tindall, Isabeau K.et. al (2021), observed the emotional strain and pressures of college and university education can produce negative emotions that may influence students' opinions on academic dishonesty and other evaluation techniques. The relationship between these attitudes and real plagiarism is still unknown, though. In two studies (Study 1: N = 718; Study 2: N = 490), the theory of planned behavior was used as a framework to examine how negative emotions affect plagiarism through attitudes, social norms, and intentions. Both investigations showed that plagiarism intentions were impacted by negative affect, with perceived norms serving as a mediating factor. Actual plagiarism behavior was then found to be predicted by intentions. These findings suggest that students may be more likely to commit academic dishonesty when they are feeling down. Higher education institutions should therefore prioritize fostering students' emotional health, especially with regard to evaluation procedures, in order to lower the likelihood of academic dishonesty.[8]

Zhang, Qinfei et. al (2022), investigates the mediating role of resilience in the connection between self-concept and negative emotions, as well as the moderating effect of exercise intensity on these relationships among college students, particularly in the context of the COVID-19 pandemic. The study involved 739 Chinese students between 18 and 25 years old, who completed assessments measuring self-concept, negative emotions, resilience, and exercise intensity. Utilizing Hayes' PROCESS macro in SPSS for analysis, the results indicated a negative correlation between self-concept and negative emotions, with resilience acting as a partial mediator. Furthermore, exercise intensity was found to moderate both the direct and indirect effects of self-concept on negative emotions, with low-intensity physical activity enhancing the relationship between self-concept, resilience, and negative emotions. These outcomes suggest that resilience serves as a crucial mechanism through which self-concept influences emotional well-being, while exercise intensity plays a moderating role. The findings underscore the importance of cultivating self-concept and resilience, as well as encouraging appropriate physical activity, as strategies to reduce negative emotions in college students.[9]

Wang et al. (2023), examines the impact of expanding negative emotion categories on the accuracy of emotion recognition using EEG and ECG data. The researchers introduce the CUMULATE dataset, which is organized into three phases, each incorporating additional negative emotions. Results show that as the number of negative emotions grows, recognition accuracy declines by more than 9%. The research identifies a reduction in the discriminative capacity of crucial EEG frequency bands (θ, α, and β), which complicates the classification process. A significant contribution of this work is the utilization of volcano plots to illustrate changes in emotional features, offering a fresh analytical approach. These findings underscore the need to balance emotional stimuli in experimental designs to enhance recognition accuracy. Future research should consider whether the inclusion of more positive stimuli could mitigate the observed classification bias. This study makes a substantial contribution to the fields of affective computing and human-computer interaction by tackling the intricacies of negative emotion recognition.[10]

Zou, Liye et. al. (2023), investigates the association between prolonged sedentary behavior and adverse emotional outcomes among 1,065 adolescent students in Shenzhen during COVID-19 lockdowns. The research utilizes DASS-21, IPAQ-SF, SSRS, and PSQI assessments to elucidate significant variations in anxiety levels, stress, social support, sedentary time, and sleep quality across gender and demographic groups. A robust correlation between sedentary behavior and negative emotions is observed ($p < .01$), which persists even when controlling for confounding variables. Notably, the study demonstrates that social support and sleep quality partially mediate this relationship. These findings underscore the significance of enhancing social connections and sleep patterns in attenuating the emotional impact of extended sedentary behavior on adolescents.[11]

According to Strohacker, Emily et. al. (2024), both traditional bullying and cyberbullying, its online equivalent, are commonplace among today's adolescents. Agnew's general strain theory (GST) has been frequently used by researchers who are trying to understand the reasons behind bullying behavior. Nevertheless, the majority of current research only looks at one emotion brought on by stress at a time. Furthermore, the causal links shown by GST have been widely and unquestioningly accepted by earlier research. The purpose of this study is to look into how socioeconomic stressors relate to negative emotions and the perpetration of conventional and cyberbullying. Socioeconomic strain is positively correlated with bullying behavior and recent negative feelings, according to research using Add Health data and path modeling in Mplus. It is noteworthy that the findings point to a possible causal chain that deviates from GST assumptions, with bullying behavior potentially impacting negative emotions instead of the other way around. The paper ends with a discussion of how these findings affect theory and policy.[12]

According to Park S. et. al. (2024), Few studies have examined the causes of negative emotions in these settings, despite the fact that they have a substantial effect on students' performance in remedial math classes at colleges. The purpose of this study was to determine whether self-regulation practices, motivating elements, and environmental variables could predict negative emotional reactions, particularly boredom, frustration, and test anxiety. 201 students from a small public institution in the Midwest who were taking a remedial math course using the adaptive system ALEKS (Assessment Learning in Knowledge Space) participated in the study. Hierarchical regression was used to analyze the data. The results showed a strong relationship between the three negative emotions assessed and motivational characteristics such as extrinsic goal orientation, task value, and self-efficacy, as well as student age (a background variable). Moreover, these negative emotional states were found to be linked to self-regulatory activities, including effort regulation and metacognitive regulation. The findings and their educational consequences are discussed in the study's conclusion.[13]

According to Guan, Jinliang et. al. (2024), For young teenagers in junior high school, suicidal thoughts represent a serious health risk. Although several studies have looked at the relationship between parenting styles and teens' suicide thoughts, few have distinguished between the effects of good and negative parenting techniques. Among Chinese junior high school students, this study examined the moderating influence of hope and the mediation role of negative emotions in the association between suicide ideation and bad parenting styles. The Parenting Style Questionnaire, Positive and Negative Affect Schedule, Children's Hope Scale, and Self-rating Idea of Suicide Scale were simplified and administered to 877 junior high school students in the Chinese provinces of Hunan, Anhui, and Jiangxi. To test the theoretical models, SPSS's PROCESS macro was used. The results showed that: (1) Suicidal ideation was favorably impacted by negative parenting approaches. (2) Suicidal thoughts and bad parenting practices were mediated by unpleasant emotions. (3) The association between suicidal thoughts and negative emotions was mitigated by hope. According to this study, preventing and avoiding teenage suicidal ideation may be accomplished through improving hope levels and resolving unfavorable parental practices.[14]

Quy, Hoang Thi Kim et. al. (2024), explores how servant leadership (SL) can improve employees' creative adaptability (CA) and lessen their negative emotions (NE) in times of crisis. In order to mediate these linkages, the study uses a proactive personality model. It also investigates if the relationship between SL and employee NE is impacted by the leader's gender. Amidst the epidemic, 315 employees of the aviation business provided data for the study. According to the results, SL has a favorable effect on CA among staff members and a negative correlation with NE. The study affirms that these correlations are mediated by proactive personality. Moreover, the effect of SL on NE was found to be moderated by the leader's gender. The ramifications of these findings are examined in the report.[15]

V. DISCUSSION

This study emphasizes how important emotion detection is for deciphering human affective states. By offering a hierarchical framework for classifying affective states, the emotional wheel improves machine-learning algorithms' effectiveness. Additionally, by providing a methodical approach to data collection, preprocessing, classification, and interpretation, the Emotion Analysis Framework strengthens the resilience of emotion identification systems. The reliability and application of these models are enhanced by datasets like DEAP, DREAMER, and AMIGOS, which provide a wide variety of affective reactions.

The ability to identify emotions in professional settings can improve worker happiness and job productivity. Issues including individual variability, categorization accuracy, and signal interference still exist despite technological progress. Multimodal techniques that include speech cues, physiological markers, and facial emotions should be investigated in future studies to increase the precision and generalizability of emotion identification systems.

VI. CONCLUSION

This study clarifies the importance of emotion detection in a variety of fields, including affective computing, mental health evaluation, learning environments, and workplace analysis, with a focus on negative affective states. Through analyzing brain activity, the study offers important new information about how emotions affect behaviour and thought processes. The Emotion Wheel and Emotion Analysis Framework are used in the study to improve the classification and understanding of emotional states, which raises the accuracy of the model. Through the development of novel applications in human-computer interaction and mental health monitoring systems, this research advances the rapidly growing field of affective computing.

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