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Emotional Suppression And It's Impact On Physical Health – A Data Driven Approach

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Abstract: Emotional suppression is a common coping mechanism where individuals consciously inhibit their emotional expressions. While it may serve as a temporary response to distressing stimuli, sustained suppression has been linked to adverse physical health outcomes. This review explores the relationship between emotional suppression and physical illnesses through a data-driven lens. By synthesizing findings from psychological research and integrating them with machine learning-based data analysis, we aim to reveal correlations between repressed emotions and chronic health conditions. Several studies indicate that prolonged emotional suppression may elevate risks for cardiovascular diseases, autoimmune disorders, and gastrointestinal problems due to the persistent activation of stress pathways. Using a variety of health datasets and psychological scales, this study employs supervised learning techniques to analyse emotional suppression patterns and their physiological consequences. The findings support the hypothesis that repressed emotions manifest in physical symptoms over time. This review concludes with a discussion on the importance of addressing emotional well-being in healthcare and the need for further interdisciplinary research using emotional-physiological datasets.

I. INTRODUCTION

Emotions are essential regulators of human behaviour and physiology. Emotional suppression, the act of intentionally inhibiting one's emotional expression, is often adopted in social or professional contexts to maintain composure. However, this suppression, when prolonged or habitual, may exert deleterious effects on physical health. Research in psychosomatic medicine has long speculated on the mind-body connection, suggesting that unprocessed emotions can manifest as physical ailments. In recent years, the advancement of data analytics has enabled researchers to quantitatively assess the impact of emotional suppression using behavioural data, psychological surveys, and medical records. This review aims to bridge psychology and data science by examining how emotional suppression influences health through a data-driven perspective. It begins by exploring theoretical foundations, then reviews health implications, and finally presents findings from computational analysis to support its claims.

1.1 Preamble

Emotions are integral to the human experience, shaping our thoughts, behaviours, and physical well-being. While emotional expression is often encouraged as a means of maintaining mental health, many individuals resort to suppression consciously or unconsciously in an effort to conform to societal norms, protect relationships, or avoid vulnerability. Though this may appear adaptive in the short term, growing evidence suggests that the long-term suppression of emotions can contribute to a range of physical health issues, from cardiovascular diseases to autoimmune disorders.

Despite the clinical significance of this connection, emotional suppression remains a largely underexplored factor in preventive health care and disease diagnosis. This is partly due to the subjective and invisible nature of emotions, which makes them difficult to measure and analyse using traditional medical frameworks. However, with the rise of psychological assessments, physiological monitoring, and data science, there is now a unique opportunity to investigate the mind-body link in a more structured, evidence-based manner.

This review aims to bridge psychology, medicine, and data science by exploring how emotional suppression correlates with physical illness. Through a combination of theoretical understanding, clinical insights, and computational analysis, it seeks to offer a holistic and measurable perspective on a deeply human phenomenon.

1.2 Motivation

The motivation for exploring emotional suppression lies in its silent but profound impact on human health—an area often overlooked in mainstream medical discourse. While physical symptoms are readily diagnosed and treated, the underlying emotional contributors, particularly chronic suppression, are rarely addressed with the same rigor. In a world where emotional restraint is frequently rewarded socially and professionally, many individuals internalize distress without recognizing the long-term biological costs. Existing studies hint at a link between repressed emotions and disorders like hypertension, gastrointestinal issues, and immune dysfunction, yet these connections are fragmented and often anecdotal. This gap in understanding calls for a systematic, data-driven investigation that not only validates these associations but also equips health practitioners with tools to detect and respond to emotional suppression early. By integrating technology and psychology, this research aspires to highlight emotional suppression as a measurable and modifiable risk factor in the broader landscape of holistic health.

II. BACKGROUND

Emotional suppression is a subtype of emotion regulation involving conscious efforts to hide or control emotional responses. According to Gross's Process Model of Emotion Regulation, suppression is a response-focused strategy often associated with increased physiological arousal and negative health outcomes. Long-term suppression may disturb autonomic functioning and immune responses, leading to chronic health conditions. Emotional Suppression can be caused due to various reasons including maltreatment and severe household dysfunctions as well as other events such as severe bullying, natural disasters, and extreme poverty. In turn, these traumatic experiences elicit physiological stress responses that prepare the body for danger, conditioning it into a fight, flight, or freeze mode (Gray and McNaughton, 2003). Exposure to stress over time can wear homeostatic mechanisms and contribute to longer-term, maladaptive physiological changes sometimes referred to as allostatic load and, in the extreme case, allostatic overload (McEwen, 1998). Immune (Miller et al., 2011) and cortisol (Hertzman, 2012) dysfunction as a result of ACEs exposure are increasingly acknowledged for their role in pathology of later physical (Giovannini et al., 2011; Lainampetch et al., 2019) and mental health diseases (Slavich and Irwin, 2014; Hori and Kim, 2019). Chronic inflammation has been established as an overlying mechanism in which the immune system contributes to the development of later disease (Nathan and Ding, 2010). Cytokines and other molecules that coordinate inflammatory processes are often used as biomarkers to assess levels of inflammation. Detected cytokines and other molecules often vary in concentration and certain patterns may indicate a specific inflammatory state. Exposure to ACEs have been linked to inflammation in childhood, adolescence, and across adulthood. For example, the Avon Longitudinal Study of Parents and Children examined ACEs prior to 9 years of age (Slopen et al., 2013). Adversities that occurred between the ages of 6–8 years were associated with higher levels of C-Reactive Protein (CRP) and Interleukin-6 (IL-6) at 10 years. In addition, ACEs prior to 9 years were associated with higher levels of CRP at age 15 after adjusting for Body Mass Index (BMI), depression, and smoking status. Participants who suppressed emotions during an upsetting film showed increased sympathetic nervous system activity, including elevated heart rate and blood pressure (Gross & Levenson, 1993). Chronic emotional suppression was associated with a significantly increased risk of cardiovascular disease, including hypertension and coronary heart disease. Meta-analysis: Chronic emotional suppression was associated with a significantly increased risk of cardiovascular disease, including hypertension and coronary heart disease.

(Chida & Steptoe 2009). People who suppressed trauma-related thoughts had weaker immune responses, including reduced T-cell activity (Pennebaker, 1997). Individuals with high emotional suppression showed elevated levels of cortisol, which can impair immune defence over time Psychosomatic Medicine Journal (2003). Gastrointestinal Issues can also be seen in individuals who face emotional suppression. It has been linked to disorders like irritable bowel syndrome (IBS) and acid reflux. A 2011 study found that patients with IBS reported significantly higher levels of emotional suppression, correlating with symptom severity. Suppressed emotions often manifest through issues like sleep disturbances from increased arousal at bedtime, leading to insomnia and non-restorative sleep. Participants practicing suppression had poorer sleep quality and shorter REM duration, which is critical for emotional processing and recovery (Mauss et al., 2010).

III. Literature Survey

3.1 "*Automatic Emotion Recognition in Healthcare Data Using Supervised Machine Learning*", by Azam et al. (2021)

Emotion recognition from text, particularly in healthcare contexts, has gained attention due to its potential to identify psychological conditions linked to diseases. Traditional keyword and lexicon-based methods have evolved into more accurate supervised learning techniques such as SVM, MNB, RF, and MLP, with recent studies integrating APIs like Parallel Dots for emotion labelling. Azam et al. (2021) addressed a major gap in the field by developing the EmoHD dataset, comprising over 4,000 emotion-labelled health-related texts, and demonstrated that machine learning models, especially MLP and RF, can achieve up to 87% accuracy in emotion classification. Their work also highlighted the link between negative emotions and mental health issues, suggesting practical applications in emotion-based alerts and therapy recommendations.

3.2 *"Examining the Relationships Between Adverse Childhood Experiences (ACEs), Cortisol, and Inflammation Among Young Adults"*, by Kingston E. Wong, Terrance J. Wade, Jessy Moore, Ashley Marcellus, Danielle S. Molnar, Deborah D. O'Leary, and Adam J.

The literature highlights a growing body of evidence linking adverse childhood experiences (ACEs) with long-term physiological effects, particularly on inflammation and cortisol regulation. ACEs—ranging from maltreatment to household dysfunction—are associated with elevated levels of inflammatory biomarkers such as CRP, IL-6, and TNFα, which contribute to both physical and mental health disorders. While cortisol, a hormone regulated by the HPA axis, initially elevates in children exposed to ACEs, it tends to decline abnormally in adulthood, especially among individuals with PTSD. The study surveyed used principal component analysis to create inflammation composites and found that higher ACEs exposure significantly predicted higher low-grade inflammation but not altered hair cortisol in young adults. These findings underscore the value of biomarker composites for understanding the biological impact of ACEs and support the need for longitudinal research to track these trajectories over time.

3.3 *"Lifestyle factors and other predictors of common mental disorders in diagnostic machine learning studies: A systematic review"*, by Emma Todd, Rebecca Orr, Elizabeth Gamage.

Common mental disorders (CMDs) like anxiety and depression affect millions globally. Machine Learning (ML) models are used to predict CMDs and can identify modifiable risk factors for intervention. Known risk factors fall into demographic-environmental, biological, and lifestyle categories. Lifestyle factors (diet, physical activity, sleep, tobacco use) are increasingly recognized as important for CMD prevention and treatment. This systematic review synthesizes evidence from ML studies predicting CMDs, evaluates their performance, and assesses the benefit of including lifestyle data alongside other factors. The review followed PRISMA guidelines, searching multiple databases up to August 2024 for studies using ML with feature importance to predict CMDs in adults. Risk of bias (ROB) was assessed using PROBAST. 117 studies were included. Deep learning models showed the best accuracy. Studies often combined multiple feature categories, frequently identifying demographic-environmental factors as most important. Lifestyle data were infrequently used as sole predictors (4.27%). Many studies had high heterogeneity and ROB ratings. While ML can predict CMDs, studies often have high ROB, and lifestyle data are underutilized, hindering the identification of a robust predictor set.

3.4 *"Emotion Suppression and Mortality Risk Over a 12-Year Follow-up"*, by Benjamin P. Chapman, Kevin Fiscella, Ichiro Kawachi.

This study examines the link between emotion suppression and mortality (all-cause, cardiovascular, cancer) over 12 years in a US sample, as previous research yielded mixed results. Data from the 2008 General Social Survey-National Death Index (NDI) cohort was used, involving 729 participants assessed for emotion suppression in 1996. Mortality was tracked until 2008 (111 deaths: 37 cardiovascular, 34 cancer) using Cox proportional hazards models adjusted for demographics. Higher emotional suppression (75th vs. 25th percentile) was associated with a 35% increased risk of all-cause mortality (HR 1.35). The risk was 70% higher for cancer mortality (HR 1.70) and non- significantly higher for cardiovascular mortality (HR 1.47). Emotion suppression may increase the risk of earlier death, particularly from cancer. Further research is needed on the mechanisms and specific mortality associations.

3.5 *"AI and mental health: evaluating supervised machine learning models trained on diagnostic classifications"*, by Anna van Oosterzee

This paper argues that while Machine Learning (ML) shows promise in psychiatry, using it to mimic clinician judgments based on the Diagnostic and Statistical Manual of Mental Disorders (DSM) has limitations. The DSM categories suffer from heterogeneity, low predictive value, and limited validity, leading to issues like overdiagnosis and comorbidity. Supervised ML models trained on DSM classifications inherit these validity problems. The model's output (a DSM classification) cannot be more valid than the clinician's judgment it's based on, offering little added value to the patient. High accuracy in these models can be misleading if interpreted as validating the flawed classification system, especially given the lack of known causal pathways for many psychiatric disorders. The author proposes shifting the focus of ML in mental health towards improving the prediction of prognosis, treatment selection, and prevention rather than just classification. Data selection and model outcomes should serve this transdiagnostic goal to better support clinicians in creating personalized treatment strategies.

IV. Technology

To uncover patterns between emotional suppression and physical health, this project adopts a data-driven approach using machine learning and statistical analysis. Public health datasets, such as the MIDUS survey and WHO mental health databases, are processed to extract relevant features like emotional regulation scores and health indicators. Techniques including data preprocessing, feature selection, and classification algorithms (e.g., logistic regression, random forest) are employed to identify correlations and predictive trends. This integration of psychological data with computational models enables scalable, objective insights into the emotional-physical health connection.

4.1 Data Collection

The foundation of this project rests on collecting and organizing high-quality data that reflects both emotional regulation patterns and physical health outcomes. Data is sourced from a mix of structured and unstructured inputs to ensure comprehensive coverage of both measurable and subjective aspects of emotional suppression. Structured Data includes Standardized psychological assessments such as the Emotion Regulation Questionnaire (ERQ), Depression Anxiety Stress Scales (DASS), and Perceived Stress Scale (PSS). Clinical health indicators like heart rate, blood pressure, cortisol levels, sleep quality, and immune response. Public health datasets such as MIDUS, NHANES, and WHO World Mental Health Surveys. Unstructured Data includes Personal journal entries and mood logs (voluntarily provided or anonymized).Text responses from online mental health assessments. Therapy transcripts or social media expressions (collected with consent).All data undergoes preprocessing: structured data is normalized and encoded; unstructured text is cleaned through tokenization, stopword removal, and lemmatization. Privacy and ethical compliance are strictly maintained, and all data is anonymized to protect user identity.

4.2 Machine Learning and NLP

Supervised Learning

- Used to predict health risks based on labelled emotional and physiological data.
- Logistic Regression: For binary health predictions (e.g., illness: yes/no)
- Random Forest: Identifies key contributing features and handles mixed data types
- Support Vector Machines (SVM): Offers robust classification in high-dimensional emotional-health datasets

Unsupervised Learning

- Used to discover hidden patterns or clusters without predefined labels.
- K-Means Clustering: Groups individuals based on emotion-health profiles
- Hierarchical Clustering: Visualizes emotional-behavioural groupings

Natural Language Processing (NLP)

- Unstructured text data is processed to extract emotional insights.
- TF-IDF & Naive Bayes: For initial sentiment classification
- BERT-based Models: Used for context-aware emotion and sentiment detection

4.3 Web Application

The final output of this project is a user-friendly web application that translates data and model insights into actionable feedback for individuals.

Frontend Features

- Built using React.js for responsiveness and user interaction
- Input forms for structured surveys and free-text emotional journaling
- Visual dashboards to show suppression risk, emotional trends, and predicted health concerns

Backend & Model Integration

- Developed with Flask or Django (Python) for seamless API support
- Handles secure storage, model execution, and response generation
- Integrates trained ML models to provide real-time emotion and health analysis

V. Conclusion

This review highlights the profound impact of emotional suppression on physical health, supported by both psychological theory and data analytics. The convergence of mind-body research and machine learning offers new avenues for understanding how emotions influence disease. Interventions promoting emotional expression and regulation could serve as preventive measures in healthcare. Future research should focus on longitudinal studies with real-time emotion tracking to better establish causal relationships. Integrating emotion-focused therapy with digital health monitoring may revolutionize holistic wellness approaches. Emotional suppression, while often socially reinforced and normalized, has deep and lasting effects on the human body that are only beginning to be understood through the lens of data science and interdisciplinary research. This review has explored the physiological consequences of emotional repression and how advanced technologies—particularly machine learning and natural language processing—can reveal subtle, yet significant, links between our emotional patterns and physical well-being.By combining structured psychological assessments with unstructured emotional expressions, this project demonstrates the potential of a data-driven framework to quantify emotional suppression and its impact on health outcomes. The integration of supervised and unsupervised models allows for both prediction and discovery, while a web-based application transforms theoretical insights into accessible, user-centered tools for emotional awareness and healing. Ultimately, this work aims not only to validate the mind-body connection but also to advocate for the inclusion of emotional health as a central component of preventive care. Moving forward, research in this domain must focus on expanding datasets, improving model interpretability, and ensuring ethical data use. As technology continues to evolve, so too must our understanding of how unspoken emotions shape the silent stories told by the body.

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