You are What (and How) you listen to.

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CERTIFICATE

It is certified that the work contained in this thesis, titled 'You are What (and How) you listen to.' by Rajat Agarwal, has been carried out under my supervision and is not submitted elsewhere for a degree.

Date

Adviser: Prof. Vinoo Alluri

To **family**, friends and

the almighty

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Abstract

Depression is a rising global mental health issue, affecting individuals worldwide. This study focuses on exploring the correlation between music engagement and depression risk, with specific attention to the "how" and "what" of music. By analyzing individuals' music preferences, consumption patterns, emotional responses, and lyrical content, this research aims to gain insights into their mental state and potential vulnerability to depression. The Healthy-Unhealthy Music Scale (HUMS) is evaluated as a non-invasive tool for assessing depression risk based on music engagement strategies. Machine learning models, such as Support Vector Machines (SVM) and deep learning techniques, are employed to predict mental well-being using music associations.

The study acknowledges the limitations of existing assessment tools, particularly the intrusive nature of some scales, and proposes the use of the HUMS scale as a promising alternative. The HUMS scale focuses on individuals' motivations and experiences with music, considering both hedonic and eudaimonic aspects of music engagement. By assessing music listening strategies on a Likert scale, it aims to capture a holistic understanding of the role of music in individuals' lives and its impact on mental health.

Furthermore, the research delves into the influence of lyrics on music engagement and its association with depression risk. It recognizes that the emotional impact of music is not solely determined by its acoustics; lyrics play a significant role in shaping the perceived emotion of a song. By analyzing the emotional connotations and semantic themes in lyrics from individuals' music listening history, the study aims to identify patterns associated with depressive mood. This analysis provides valuable insights into the influence of lyrical content on emotional well-being, enhancing our understanding of the complex relationship between music and mental health.

Machine learning models are employed to analyze lyrics to determine their emotional connotations in an automated fashion and also to predict risk to depression based on consumption strategies. These models aim to identify potential markers of depressive tendencies and predict an individual's risk of depression based on their music engagement data. The use of advanced algorithms, such as Support Vector Machines (SVM) and deep learning techniques, enables the development of predictive models that can assess depression risk through music.

The findings of this study have significant implications for the field of mental health assessment and intervention. Validating the HUMS scale as a depression screening tool in the Indian context contributes to non-invasive and culturally sensitive approaches to detecting depression risk. The application of machine learning models to predict mental well-being based on music associations offers new possibilities for personalized interventions and early detection methods. Moreover, exploring the relationship between lyrics and depression risk expands our understanding of the emotional impact of music beyond its acoustic properties.

This interdisciplinary research merges computer science, psychology, and musicology to explore the intricate relationship between music and mental health. By bridging the gap between technology and mental health, the study aims to drive innovation and create effective tools for assessing and addressing depression risk through music engagement. The outcomes of this research have the potential to make a positive impact on individuals' lives by helping to alleviate the global burden of depression.

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Chapter 1

Introduction

1.1 Depression in India: A Rising Global Mental Health Issue

Mental disorders are on the rise all over the world owing to unprecedented social and economic changes. Disturbingly, depression has become a prevalent global mental health concern, affecting individuals of all ages and backgrounds. In India, mental illness in general accounted for 31 million Disability-adjusted life-year (6% of overall disease burden) of which 37% is due to depressive disorders [1] As per the latest estimates, 57 million people were affected by depression in India and is projected to be the leading cause of disease burden in by the end of the next decade by WHO. Despite the unprecedented prevalence of depression in India, the stigma associated with depression poses to be one of the biggest challenges for a timely intervention [1]. Consequently, depression goes unacknowledged, undetected and hence untreated engendering marked impact in crucial areas of life including family, work place, and social relations. Encouragingly, depression is to a great extent preventable and treatable provided it is detected at early stages. Therefore, there is a need to find indirect and unsuspecting ways to identify risk for depression in individuals and provide timely intervention

1.2 Depression Risk assessment

Several tests and assessment tools are used to evaluate depression risk. One widely used instruments include the K10 scale [2].

1.2.1 K10 Assessment scale

The K10 scale is a widely used psychological assessment tool designed to measure psychological distress, including symptoms of depression, anxiety, and stress. Developed by Kessler et al. in 2002, the K10 scale provides a quick and reliable self-report measure for evaluating an individual's mental health status. The K10 scale consists of ten questions that inquire about the frequency of specific emotional states and experiences over the past four weeks. The questions cover aspects such as feeling nervous, feeling hopeless, and experiencing fatigue. Each item is scored on a five-point Likert scale, ranging from 1 (none of the time) to 5 (all of the time). The total scores on the K10 scale can range from 10 to 50, with higher scores indicating a higher level of psychological distress. The scale allows for the classification of individuals into different risk categories based on their scores. For example, scores between 10 and 19 suggest low distress, scores between 20 and 24 indicate moderate distress, and scores of 25 or higher indicate high distress. The K10 scale has been widely used in clinical and research settings to assess psychological distress and identify individuals at risk for various mental health conditions, including depression. It provides a relatively simple and efficient way to screen for symptoms of depression and other psychological disorders. One of the advantages of the K10 scale is its brevity and ease of administration. It can be self-administered or administered by a healthcare professional, making it a practical tool for large-scale surveys and clinical settings. Additionally, the K10 scale has demonstrated good reliability and validity in measuring psychological distress across different populations and cultural contexts. The K10 scale is not intended to provide a definitive diagnosis but serves as an initial screening tool to identify individuals who may require further assessment or intervention. It can be used to monitor changes in distress levels over time and assess the effectiveness of interventions.

However, one significant drawback of K10 is the potential intrusiveness and invasiveness of the questions asked. The K10 includes inquiries about personal experiences of psychological distress, such as feeling tired, nervous, or worthless. These questions may touch upon sensitive and intimate aspects of an individual's mental well-being, which can be uncomfortable or distressing for some respondents.

The intrusive nature of the questions in the K10 may lead to response biases, where individuals may be hesitant to disclose certain symptoms or emotions due to social desirability or concerns about stigma. This could result in an underreporting or misrepresentation of the individual's true level of psychological distress. Additionally, the personal nature of the questions may cause discomfort or emotional distress for individuals who are already vulnerable or experiencing heightened sensitivity.

Thus there is a need to develop indirect and non-intrusive ways to detect the risk of depression, so that timely interventions can be made and the resulting disease burden contained. How a person engages with music has been a topic of interest in this regard.

1.2.2 Examining Music: An Indicator of Depression Risk

Recent research has shown that the engagement with music can serve as a valuable indicator of an individual's mental state, particularly in relation to depression risk. Music has a profound impact on emotions, mood regulation, and overall well-being [5]. The way individuals engage with music, including their music preferences, consumption patterns, and emotional responses, can provide insights into their psychological state and potential risk for depression.

Studies have revealed that certain patterns of music engagement are associated with depressive symptoms. For instance, individuals who predominantly listen to music that reinforces negative emotions or thought patterns may be more susceptible to depressive tendencies [4]. On the other hand, those who use music for self-care, emotional expression, and relaxation demonstrate higher emotional resilience and reduced depression risk [7].

By examining the music engagement of individuals, researchers can gain valuable insights into their mental state. This can be accomplished through various means, including self-report assessments, analysis of music listening histories, and examination of music-related behaviors on digital platforms [3]. These methods allow for a more objective and comprehensive understanding of an individual's relationship with music and its potential implications for mental health.

Machine learning approaches have been employed to analyze music engagement data and predict mental states, including depression risk, with promising results [22]. By leveraging advanced algorithms and models, researchers have been able to identify patterns and associations between music engagement features and mental health outcomes. This enables the development of predictive models that can assess an individual's depression risk based on their music engagement data.

Understanding the link between music engagement and depression risk provides opportunities for timely intervention and support. It allows for the development of personalized interventions that leverage the positive aspects of music to promote well-being and mitigate depression risk [22]. By identifying individuals at risk for depression through their music engagement, targeted interventions can be tailored to address their specific needs and provide timely support [7].

In conclusion, engagement with music offers valuable insights into an individual's mental state, including their risk for depression [4]. By examining music preferences, consumption patterns, and emotional responses, researchers can gain a deeper understanding of an individual's psychological well-being. This understanding opens doors for early detection, intervention, and the development of personalized approaches to promote mental health and well-being.

However, while researching this, a distinction must be made on the impact of the kind of music one listens to vs the music consumption strategies one employs while engaging with music -

1.2.2.1 The "How" of Music - How one engages with music.

Music has the ability to evoke various emotions. When used as a form of self-therapy for individuals facing difficulties or challenging events in their lives, music has the potential to address mental health issues and help individuals cope with their emotions [33]. However, research has revealed that people sometimes engage with music in ways that can be counterproductive [34] [35], leading to negative consequences [36] [31] or associations with mental illnesses like depression, particularly among adolescents and adults in western societies [37] [38] [31] [13]. In such cases, music listening with the goal of rumination, avoidant coping [36] [31] or perpetuating social isolation results in reinforcement or escalation of negative mood states and ultimately leading to a decline in overall well-being of the individual [39]. On the other hand, adaptive music listening behaviors such as using it for reappraisal, healthy distraction, and problem solving or as a relaxation tool have been found to have a positive impact on well-being [40] [31] [41] .

1.2.2.2 The "What" of Music - What kind music does one listens to

The relationship between an individual's music preferences and their risk of depression has been a topic of research interest. While findings have been mixed, some studies suggest associations between certain music genres, the music listening behaviors and depressive symptoms. Hence, both the factors- 'how' a music is consumed, and 'what' kind of music is consumed seem to play a bearing on the proneness to depression in an individual.

1.2.3 HUMS - Healthy Unhealthy Music Scale

The Healthy-Unhealthy Music Scale (HUMS) is an assessment tool that aims to explore the relationship between music listening strategies and psychological well-being. Developed by Van den Tol et al. in 2018, the HUMS scale focuses on understanding the hedonic (pleasure-based) and eudaimonic (meaning-based) motives for listening to music and their impact on individuals' mental health. HUMS was developed, albeit on Australian adolescents, as a non-intrusive tool which allows for indirectly measuring susceptibility to depression and levels of psychological distress based on music listening strategies [13]. The HUMS or Healthy-Unhealthy music scale is a 13-item (Table 1.1) long assessment that aims to assess music engagement strategies of the responder on a 5-point Likert scale with 1 representing Highly Disagree and 5 Highly Agree. Using factor analysis, the 13-items are divided into two main dimensions depicting "Healthy" and "Unhealthy" music listening strategies. It was observed that individuals scoring high on the Unhealthy factor also scored high on K10 as evidenced by the significant positive correlation. Therefore, HUMS can be a viable alternative to detecting risk of depression and psychological distress in a non-invasive fashion. However, the validity of HUMS has not been investigated in an Indian context. Furthermore, with the advent of more sophisticated AI/ML models, responses to HUMS items have great potential to be an apt set of features for AI/ML based software that is capable of flagging people with depressive tendencies and psychological distress. Another interesting thing to explore would be whether the underlying patterns that the ML model identifies from Indian data is similar to patterns in Australian data.

		Never	Rarely	Some-times	Often	Always
1.	When I listen to music I get stuck in bad memories	☐	☐	☐	☐	☐
2.	I hide in my music because nobody understands me, and it blocks people out	☐	☐	☐	☐	☐
3.	Music helps me to relax	☐	☐	☐	☐	☐
4.	When I try to use music to feel better I actually end up feeling worse	☐	☐	☐	☐	☐
5.	I feel happier after playing or listening to music	☐	☐	☐	☐	☐
6.	Music gives me the energy to get going	☐	☐	☐	☐	☐
7.	I like to listen to songs over and over even though it makes me feel worse	☐	☐	☐	☐	☐
8.	Music makes me feel bad about who I am	☐	☐	☐	☐	☐
9.	Music helps me to connect with other people who are like me	☐	☐	☐	☐	☐
10.	Music gives me an excuse not to face up to the real world	☐	☐	☐	☐	☐
11.	It can be hard to stop listening to music that connects me to bad memories	☐	☐	☐	☐	☐
12.	Music leads me to do things I shouldn't do	☐	☐	☐	☐	☐
13.	When I'm feeling tense or tired in my body music helps me to relax	☐	☐	☐	☐	☐

Scoring instruction: HUMS Healthy: 3, 5, 6, 9, 13; HUMS Unhealthy: 1, 2, 4, 7, 8, 10, 11, 12. Answers are scored on a scale from 1 (never) to 5 (always).

Figure 1.1: HUMS

1.3 HUMS: Advantages of a non-invasive test

Non-invasive tests, such as the HUMS scale, offer advantages over more intrusive assessments like the K10 scale. The HUMS scale allows individuals to express their motivations and experiences with music, focusing on the positive aspects of music engagement rather than solely distress levels. It provides a holistic understanding of the role of music in an individual's life, considering its potential benefits for mental health and well-being. This approach can foster a more open and nuanced exploration of emotional experiences related to music, potentially enhancing engagement and accuracy of assessment.

1.4 Role of Lyrics

An important but comparatively less studied topic pertains to 'what' kind of music is consumed ie. the lyrics or the content of the music. The influence of music on emotions is widely acknowledged, with lyrics playing a vital role in this impact by offering meaning and emotional connotations that interact with the acoustic characteristics of the music. Past studies have primarily examined the acoustic properties of music preferred by individuals at risk for depression, revealing a tendency towards low valence and low energy music. However, it is important to note that the emotional impact of music is not solely determined by its acoustics, as lyrics also hold significant influence in shaping the perceived emotion of a song. For instance, a study by Rentfrow and Gosling (2003) [11] found that individuals with higher depression scores were more likely to listen to sad or melancholic music. Thus, there is a scarcity of research focusing on the connection between music lyrics, particularly the semantics and emotional connotations of lyrics, and depression. Our study aims to fill this gap by investigating the association between music lyrics and depression.

1.5 AL/ML models or techniques being used to predict risk of depression through music

The emerging field of utilizing artificial intelligence (AI) and machine learning (ML) models to predict depression risk through music shows promise for advancing mental health assessment. These models analyze various features of music, such as acoustic properties, lyrical content, and sentiment analysis, to identify potential markers of depressive tendencies. By training algorithms on large datasets that include music preferences and mental health outcomes, these models can learn to recognize patterns and predict an individual's risk of depression. However, it is important to note that this field is still in its early stages, and further research is needed to refine and validate these models. Challenges include the inherent subjectivity of music preferences and the complex nature of depression. Future advancements in AL/ML techniques, along with interdisciplinary collaborations between computer scientists, psychologists, and music experts, may contribute to more accurate and reliable predictive models for assessing depression risk through music. Several approaches in this context have been explored:

- Feature-based Analysis: This approach involves extracting various features from music, such as acoustic properties (tempo, rhythm), spectral characteristics, and emotional content. Machine learning algorithms are then trained on these features to classify music into categories associated with depression risk.

- Sentiment/Emotion Analysis: Sentiment analysis focuses on analyzing the emotional content of music, including the lyrics and audio signals, to detect sentiment patterns related to depression risk. Natural language processing (NLP) techniques are commonly used to extract sentiment information from lyrics, while audio signal processing methods analyze acoustic cues related to emotional expression.

- Deep Learning: Deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been applied to learn complex patterns and representations from music data. These models can capture intricate relationships between music features and depression risk, enabling more accurate predictions.

- Multi-modal Approaches: Some studies have explored combining multiple modalities, such as audio and lyrics, to create a more comprehensive representation of music. By integrating information from different sources, these models aim to capture a richer understanding of music and its potential relationship with depression risk.

- Collaborative Filtering: Collaborative filtering techniques leverage user preferences and behavior to make predictions. By analyzing patterns of music preferences and depressive symptoms in large-scale datasets, recommendation systems can be developed to identify individuals at risk based on their music listening patterns.

The effectiveness of these approaches will depend upon the availability of high-quality, well-annotated datasets and the integration of domain expertise from psychology and musicology with AI/ML methodologies.

1.6 Scope and objectives of the present study

Music is commonly used across cultures to evoke positive emotions and moods. While some individuals use music as a therapy, others may adopt maladaptive strategies such as rumination, avoidant coping, or social isolation as they listen to music. Additionally, lyrics also play a significant role in determining the perceived emotion and hence the effect of a song on one's emotional state. Thus, the “How” of Music ie. how one engages with music, as well as the “What” of Music ie. the lyrical content of the music affects and reflects the mental state and mood of an individual. While the Healthy-Unhealthy Music Scale (HUMS) has been developed as an assessment tool in the Australian population to gauge anxiety levels and potential risk for depression using music engagement ie. the ‘How’ of the music, its validity in an Indian context needs to be established. Further, we hypothesize that machine learning models have the potential to capture the underlying pattern and can be employed to predict mental well-being based on music associations. Our specific objectives to address the ‘How’ of Music are as follows:

1. To examine the applicability of HUMS as a depression screening tool in an adult population using statistical methods used originally.
2. To employ machine learning models like SVM, Neural network, Linear and Logistic regression to establish predictive validity of HUMS.
3. To employ powerful models like SVM and deep learning to assess feasibility of AI based depression diagnosis using HUMS.

Secondly, in this study, we aim to explore whether an individual’s music listening history, particularly with regard to lyrics, correlates with the risk for depression. Through analysis of the lyrics of the songs individuals listen to, we aim to deepen our understanding of the emotional content that is closely associated with depressive mood. We hypothesize that lyrics associated with individuals at risk for depression will exhibit emotions characterized by low arousal and low valence, indicative of depressive mood. Our specific objectives for the ‘What’ of Music are as follows:

1. To analyze emotional connotations in lyrics from individuals’ music listening history and identify patterns related to depression risk.
2. To investigate the presence of semantic themes in lyrics of songs individuals listen to and explore their association with depression risk.

Chapter 2

HUMS: Predicting Depression Non-invasively in India

2.1 "How" of Music to depression risk

The impact of music on mental wellbeing has long been recognized, but recent research suggests that how individuals engage with music is as important as the specific genre or type of music they listen to. This notion highlights the multifaceted nature of music's influence on our emotional and psychological states. By examining the ways in which individuals engage with music, we can gain valuable insights into its potential effects on mental wellbeing.

2.1.1 Importance of Music Engagement:

The raw text doesn't provide any numeric information to the machine. The text has to be represented in a meaningful numeric way for machines to interpret. There are representations which take the order of the words into consideration (contextual representations) and which don't take the order of the words into consideration (context-free).

2.1.1.1 Active Listening:

Engaging with music actively, such as through focused listening or music-making, has been associated with positive psychological outcomes. According to a study by Linnemann et al. (2020), active music engagement is linked to improved mood, enhanced well-being, and increased social connectedness. Actively engaging with music allows individuals to fully immerse themselves in the experience and derive emotional and cognitive benefits.

2.1.1.2 Emotional Connection:

The emotional connection individuals have with music plays a crucial role in their mental wellbeing. Music has the power to evoke a wide range of emotions, including joy, sadness, and nostalgia. Research by Saarikallio and Erkkilä (2007) [16] found that music-induced emotions can have a significant impact on individuals' psychological states and can be used as a coping mechanism during challenging times. Individuals who actively seek out music that resonates with their emotional needs may experience greater psychological well-being.

2.1.1.3 Personal Meaning:

The meaning individuals attribute to music can greatly influence their mental wellbeing. Personal experiences, memories, and associations with specific songs or lyrics can evoke powerful emotions and provide a sense of comfort and identity. According to research by [4], music that holds personal significance has the potential to serve as a source of solace, self-expression, and emotional catharsis.

So in essence, understanding the importance of music engagement beyond genre preferences is essential for comprehending its impact on mental wellbeing. Active listening, emotional connection, social aspects, and personal meaning are all integral components of music engagement that influence psychological outcomes. By recognizing these dimensions and their effects, we can develop interventions and strategies that harness the positive benefits of music for mental health promotion.

2.2 HUMS - Background and limitations

The Healthy-Unhealthy Music Scale (HUMS) examines the relationship between music engagement and depression risk. HUMS recognizes that music profoundly influences emotions, mood regulation, and stress levels. It assesses various aspects of music preferences and consumption patterns to uncover potential links to mental health.Research suggests that specific music listening strategies and preferences can be associated with depression risk. For example, individuals who engage with music evoking negative emotions may be more susceptible to depressive tendencies. Conversely, using music for self-care and emotional support can enhance resilience and reduce depression risk. HUMS captures these nuances by evaluating preferred music types, emotional responses, listening frequency, and social context. The Unhealthy factor of HUMS, reflecting maladaptive music engagement, has shown a positive correlation with depression risk measures. Understanding the relationship between music engagement, as measured by HUMS, and depression risk informs interventions and support. It enables tailored approaches to promote healthier music engagement patterns and emotional well-being. Furthermore, HUMS insights can guide the development of targeted music-based interventions to reduce depressive symptoms and enhance mental health. However, it is important to note the limitations of HUMS. The scale was initially developed on an Australian population, primarily focusing on adolescents. Generalizing its findings to different populations and age groups requires further validation and adaptation.

2.3 Motivation and Objectives

The prevalence of mental disorders, including depression, has been on the rise globally, posing significant challenges to individuals' well-being. In India, mental illness accounts for a considerable portion of the disease burden, with depressive disorders contributing significantly to this burden. Unfortunately, due to the stigma associated with depression, it often goes unnoticed, undetected, and untreated, resulting in adverse impacts on various aspects of individuals' lives, such as family, work, and social relationships. Early detection of depression is crucial for timely intervention and effective treatment. However, the traditional assessment tools for depression risk, such as the Kessler's Psychological Distress Scale (K10), may be perceived as invasive and may not be readily embraced by individuals, particularly in cultural contexts like India. To address these challenges, there is a need for indirect and non-intrusive methods to identify individuals at risk of depression and provide timely intervention. Music, being a universal language and an integral part of human culture, has been shown to have a profound impact on mental health and well-being. Engaging with music can serve as a coping mechanism, providing emotional solace and catharsis during challenging times. Music therapy has also demonstrated effectiveness in reducing depressive symptoms and improving overall mental health. Given these associations between music and mental well-being, there is a growing interest in exploring the relationship between music preferences, consumption strategies, and depression risk. The Healthy-Unhealthy Music Scale (HUMS) is an assessment tool that measures music engagement strategies and has been developed as a non-intrusive means of indirectly assessing susceptibility to depression and levels of psychological distress. Previous research conducted in Australia has shown promising results, indicating a positive correlation between high scores on the Unhealthy factor of HUMS and elevated scores on the K10, suggesting the potential of HUMS as an alternative tool for detecting depression risk. However, it is important to revalidate the applicability and effectiveness of HUMS in a different cultural context, such as India, where the socio-cultural factors and music preferences may differ. Furthermore, recent advancements in Artificial Intelligence and Machine Learning (AI/ML) present an opportunity to leverage HUMS responses to develop predictive models for depression risk assessment. These models can potentially provide valuable insights into the underlying patterns and help identify individuals at risk of depression more efficiently.

Objectives:

- Revalidate the applicability and external validity of HUMS in an Indian context by examining its structure through Exploratory Factor Analysis (EFA) and assessing its concurrent validity through correlations with depression risk and mental well-being measures.

- Develop and employ AI/ML models, such as Support Vector Machines (SVM), Neural Networks, and Regression analysis, using HUMS responses as features to establish the predictive validity of HUMS for depression risk assessment.

- Explore the feasibility of using AI/ML models, including SVM and deep learning techniques, to develop an AI-based software capable of diagnosing psychological distress and predicting depression risk using HUMS.

By revalidating HUMS in an Indian context and leveraging AI/ML techniques, this study aims to enhance our understanding of the relationship between music preferences, consumption strategies, and depression risk. Ultimately, the development of a predictive model based on HUMS responses could provide valuable insights and support timely interventions for individuals at risk of depression, contributing to a more mentally healthy society.

2.4 Methods

2.4.1 Participants

A total of 292 adults participated in the survey (mean age = 26.88, sd = 6.02). Half of the sample (ID1 - 151 individuals) belonged to a working population and the other half (ID2 - 141 individuals) comprised mainly students engaged in post-graduate and doctoral studies. We chose adults instead of adolescents as consent for minors to take part in the survey is an elaborate process which requires parents' permission. Moreover, previous research indicates that there are no significant differences between adolescents and adults in terms of the patterns that specifically link music listening patterns to depression (Saarikallio, Suvi, Gold , Christian McFerran, Katrina, 2015; McFerran, K. S., Saarikallio, S.,2013).

2.4.2 Data

Data was collected through online surveys. The survey comprised 13 items from HUMS, 10 from standard K10 survey and 14 from standard Mental Health Continuum short form (MHCSF) assessment. The analyses were performed on the combined dataset (ID = ID1 + ID2). Data from the original study (Saarikallio, Suvi, Gold , Christian McFerran, Katrina, 2015) comprised 211 Australian adolescents with a mean age of 13.75 years and a standard deviation of .72 years. (AD).

2.4.3 Testing Validity

The data was analyzed using conventional statistical techniques in R and Python. Initially, exploratory factor analysis was conducted on the individual Indian datasets (ID1 and ID2) separately, as well as on the combined dataset (ID = ID1+ID2), to uncover the underlying structure of HUMS. The results were then compared with the findings of the original study. Following that, concurrent validity analysis was performed by examining the correlations between the factor scores obtained in the previous step and the scores from standard assessments such as K10 and MHCSF.

2.4.4 Modeling psychological distress and depression from HUMS

To investigate the possibility of predicting K10 scores using the individual HUMS items, a stepwise linear regression analysis was conducted. This approach enabled the assessment of the relative importance of each question in predicting K10 scores.

Next, the participants were categorized into four groups [42] based on their K10 scores. Various machine learning techniques, including linear Support Vector Machine (SVM), non-linear SVM, and multilayer feedforward neural networks, were employed to predict K10 scores using the HUMS data. These approaches were compared based on their in-sample error and out-sample error using a 10-fold cross-validation with 10% of the data held out. These analyses were performed on the combined datasets (ID + AD). Due to the inherent imbalance in the collected data, with fewer samples in the higher ranges of the K10 distress category, several techniques such as under-sampling and oversampling were attempted. Additionally, ensemble-based classifiers were evaluated. Moreover, in order to address the imbalance issue, the analyses were repeated using two categories instead of four. This involved combining the first two and last two categories of the original four-class model [42]. The aim was to simplify the model and enable effective learning with a smaller amount of data.

A two-category classification allowed for the identification of higher-risk individuals falling into the second category, exhibiting moderate to high K10 scores. These individuals would greatly benefit from further clinical evaluation and possible early intervention for the identified condition.

2.5 Results

In order to evaluate the intrinsic dimensionality of our datasets we employed one of the most commonly used estimation methods, which is based on the Eigenvalues satisfying the Kaiser criterion (1960). As a result, two intrinsic dimensions were observed as in the original study. Factor analyses revealed highly similar loading patterns in the individual and combined Indian datasets and were close to being identical to the underlying structure of AD. Hence, the combined Indian dataset ID was used for subsequent analyses in order to increase statistical power of hence obtained results. Figure 2.1 displays the factor loadings for both ID and AD for the “Healthy” and “Unhealthy” factors. The two factors will be referred to as Unhealthy and Healthy for the reminder of the study.

Table 2.1 displays the correlation pattern between the factors for both ID and AD. Pearson correlations revealed significant positive correlation between Unhealthy factor scores and K10 scores. However, Healthy factor scores were found to correlate significantly with well-being as measured by MHCSF only in ID.

Table 2.1: *Pearson correlations between HUMS Healthy, Unhealthy, K10 and MHCSF. U: Unhealthy factor score, H: Healthy factor score; *p < .05; **p < .01; ***p < .001*

	ID		AD	
	H	U	H	U
H	1	.17**	1	.16*
U	.17**	1	.16*	1
K10	0.06	.52***	.19*	.68***
MHCSF	.30**	'-.15	0.08	'-.49***

Multivariate linear regression performed using the unhealthy items (U1-U8) revealed that a relatively high amount of variance could be explained in AD (adjusted R 2 = 47%) while a moderate amount could be explained in ID (adjusted R 2 = 31%). Adding the Healthy items (H1-H5) in the model resulted in an increase in variance explained, albeit marginal and non-significant. These results hint at the existence of potential non-linear combinations of HUMS items in predicting K10. Due to high concurrent validity of HUMS with K10 in an Indian setting and highly similar factor structure between both the Indian and Australian datasets, subsequent analyses were performed on combined data (AD + ID). The combined data was divided into 4 classes based on K10 score as described in Victorian Population Health Survey, 2001. The Unhealthy items were used as predictors for K10 scores. The classification accuracy using SVM and other linear and nonlinear modeling approaches can be seen in Table 2.2.

Table 2.2: Classification accuracy of various classification models using Unhealthy HUMS items for K10 4-class K10 predictions using the combined dataset. *size of hidden layers in the network

Model	In sample accuracy (training)	Out sample accuracy (testing)
SVM - Linear	58.3	56.2
SVM - RBF (SVM - RBF with all HUMS items)	93 (99.2)	54.5 (55.3)
Neural Net (13,13,3)*	70.4	56.2
Logistic regression	59.2	56

Since SVM – RBF (radial basis function) demonstrated highest in-class accuracy, we repeated the analysis with all HUMS items as predictors and achieved a training accuracy of 99% (row 2 of Table 2.2). The confusion matrix (Figure 2) for the in-sample accuracy of SVM-RBF with HUMS as predictors illustrates near perfect accuracy for every class.

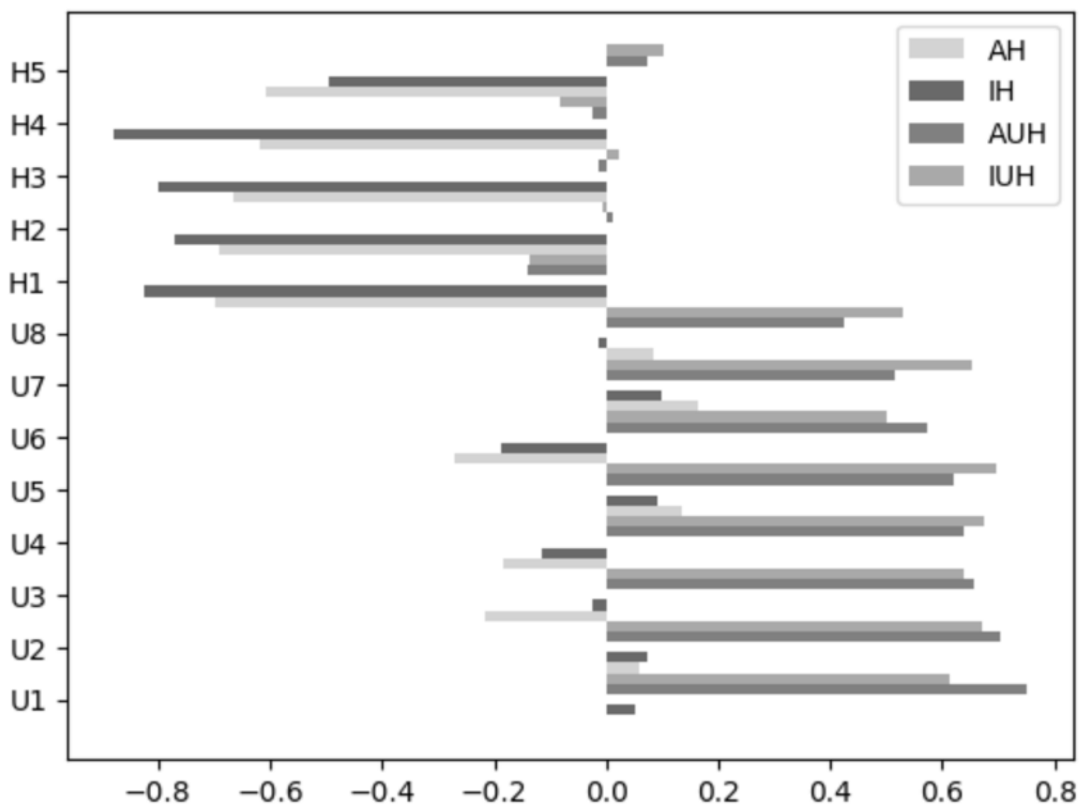

Figure 2.1: Factor loadings of the Australian and Indian sample. The loadings for the healthy factor have been reversed in sign for representational purposes. IUH: Indian Unhealthy Factor, AUH: Australian Unhealthy Factor, IH: Indian Healthy Factor, AH: Australian Unhealthy Factor

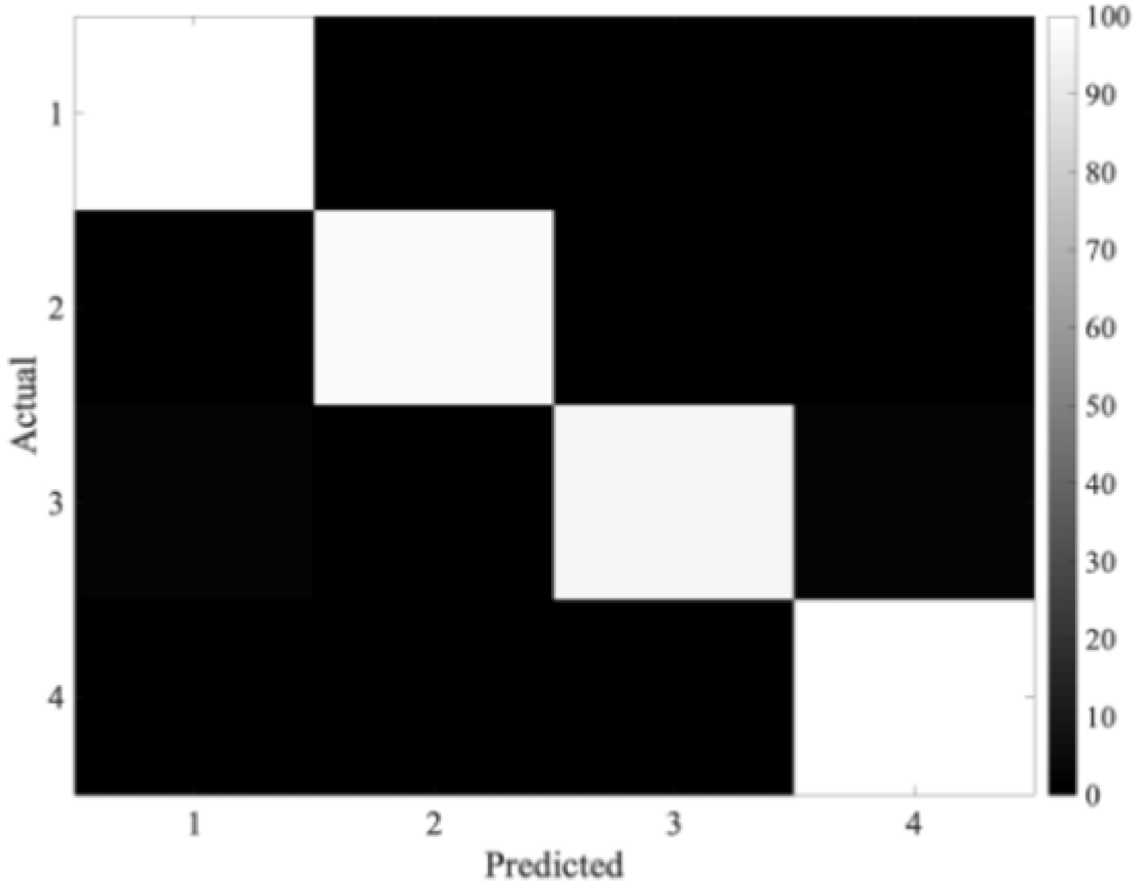

Figure 2.2: Training data Confusion Matrix

This presents some additional evidence of existence of a non-liner mapping between HUMS and K10. However, the accuracy for test data is limited to 55% (Table 2.2). The accuracy did not improve much even after extensive hyper parameter tuning of SVM (non linear). Hyper parameter tuning for neural network was not attempted due to limited training data being available. One potential explanation for the low generalizability is the imbalance of class-wise training data. Since the data was not collected from a clinically diagnosed sample, the probability of obtaining sufficient data in classes 3 & 4 is relatively low in comparison to class 1 & 2 (n=274 for class 1, n=107 for class 2, n =57 for class 3 and n=65 for class 4). Hence, in order to minimize the under representation of classes 3 & 4, techniques such as oversampling data of the minority class (class 3 & 4) data or undersampling that of the majority category data were employed (Guillaume Lemaitre, Fernando Nogueira, Christos K. Aridas, Imbalanced -learn, 2016). Furthermore, since classes 3 & 4 represent high-risk population who require further clinical evaluation, the classification problem was converted to a 2-category problem by combining classes 1 & 2, and classes 3 & 4 respectively. Table 4 displays the results of the undersampling and oversampling techniques for both 4-class and 2-class classification. Specifically, in order to minimize overfitting and increase generalizability of the models, training was performed on ID and tested on AD and vice versa. As can be seen in Table 2.3, the results of a 2-class classification range are found to be significantly higher than chance level reaching a maximum accuracy of 81%. Similarly, the model trained on AD and tested on ID revealed a 2-class accuracy of 77%. These results imply that music listening strategies indeed have universals, which can be learnt using machine learning models.

Table 2.3: Comparison of various undersampling and oversampling techniques and classifiers with unbalanced data. The results are out of sample accuracy percentages by training on ID data and testing on AD

Model	4-class	2-class
SVM (rbf) with Random oversampling	45.97	78.67
SVM (rbf) with SMOTE	47.87	78.2
SVM (rbf) with ADASYN	43.6	75.83
SVM (rbf) with random undersampling	48.34	76.78
SVM with undersampling using NearMiss	25.59	70.62
BalancedRandomForestClassifier	47.39	81.04

2.6 Conclusions:

HUMS demonstrates high validity in the Indian adult population to assess psychological distress and potential risk for depression and other mental disorders . Very low training error and high accuracy points towards the existence of a non - linear function that maps the HUMS responses to K10 score. Existence of such a function adds to the aptness of HUMS as a mental state detector. To add to this, the high predictive power of the machine learning models , especially in the 2 -class problem (as evidenced by significantly high classification accuracy for the moderate to high -risk groups) , further increases the generalizability of HUMS in a global context. Thus, HUMS can be used as a comprehensive and valid instrument to employ in the Indian context as a non -invasive tool to assess mental well -being thereby circumventing the stigma associated with direct assessment and discussion related especially to depression . This has potential implications in a corporate setting wherein detecting internal states and potential risky behavior in employees is vital for constructive intervention

Chapter 3

Lyrics to Depression risk.

3.1 Introduction

The type of music one listens to plays a crucial role in the relationship between music and depression risk. Research has shown that certain music genres, such as sad or melancholic music, may be associated with increased risk of depressive symptoms [15]. Individuals who frequently engage with music that evokes negative emotions or reinforces negative thought patterns may be more susceptible to depressive tendencies. Conversely, music with positive and uplifting themes has been found to have a beneficial effect on mental well-being [21].

However, it's not just the genre or general characteristics of the music that matter. The emotional connotations of lyrics in songs also significantly contribute to the connection between music and depression risk. Lyrics have the power to evoke specific emotions, resonate with personal experiences, and provide a means of self-expression for both listeners and songwriters. When individuals strongly identify with the emotional content of lyrics, it can have a profound impact on their mental well-being.

Songs with lyrics that reflect feelings of sadness, despair, or hopelessness may resonate with individuals who are experiencing or susceptible to depression. The lyrics may provide a sense of validation, offering solace and a sense of understanding to those who are going through difficult times. However, prolonged exposure to lyrics with predominantly negative emotional connotations can potentially reinforce negative thought patterns and contribute to the risk of depression [23].

On the other hand, music with lyrics that convey positive and uplifting themes, such as resilience, empowerment, or hope, can have a beneficial effect on mental well-being. These lyrics may inspire feelings of optimism, motivation, and emotional strength, serving as a source of support and encouragement for individuals struggling with depression or at risk of developing depressive symptoms [20].

It's important to note that the impact of lyrics on depression risk can vary among individuals. Personal experiences, cognitive biases, and individual differences in emotional regulation can influence how individuals interpret and respond to lyrical content. What might be uplifting and empowering for one person may have a different effect on another.

In conclusion, the kind of music one listens to, including both the genre and the emotional connotations of lyrics, is closely tied to the risk of depression. Music that evokes negative emotions and reinforces negative thought patterns may contribute to depressive tendencies, while music with positive and uplifting themes can provide emotional support and promote mental well-being. However, the relationship between music, lyrics, and depression risk is complex and can vary among individuals. It is essential to consider individual differences and personalized approaches when using music interventions for mental health support.

3.2 Objective, Motivation, and Hypothesis:

This study aims to explore the relationship between lyrical content preferences in the online music consumption of individuals at risk for depression and their risk of depression. The objective is to investigate whether people's music listening history, specifically in terms of lyrics, correlates with the risk for depression. By analyzing the emotional connotations and semantic features extracted from lyrics, the study seeks to uncover patterns and trends in lyrical content that are associated with depressive mood and risk of depression. In essence the following are the objectives:

- To analyze emotional connotations in lyrics from individuals' music listening history and identify patterns related to depression risk.

- To investigate the presence of semantic themes in lyrics of songs individuals listen to and explore their association with depression risk.

The motivation behind this research is rooted in the recognition of the significant impact of music on mental well-being and the understanding that lyrics play a crucial role in shaping the emotional experience of music. Previous studies have primarily focused on analyzing the acoustic properties of music consumed by individuals at risk for depression, while the contribution of lyrical content to the emotional impact of music has received less attention. By examining the emotional connotations of lyrics and their connection to depression risk, this study aims to fill this research gap and provide a deeper understanding of the emotional aspects of music that are most closely associated with depressive mood.

Understanding the emotional connotations of lyrics and their relationship to the risk of depression is crucial for developing targeted interventions and support systems for individuals with depressive tendencies. The hypothesis is that individuals at risk for depression prefer songs with low valence and low arousal, as determined by lyrics, which is consistent with previous studies on acoustic features. Additionally, it is hypothesized that individuals at risk for depression prefer lyrical content high in themes such as Denial, Self-reference, Ambivalence, and Tenacity, while themes such as Liberation and Familiarity are not as favored.

The unavailability of similar research exploring the specific relationship between lyrics and depression risk highlights the need for this study. While previous studies have examined the impact of music on mental health outcomes, the focus on lyrics and their emotional connotations in relation to depression has received limited attention. This study seeks to bridge this research gap and contribute to a more comprehensive understanding of how lyrical content influences emotional states and the risk of depression.

The findings from this study can have significant implications for the development of personalized music-based interventions and recommendations that leverage the emotional power of lyrics to support mental well-being. By gaining insights into the emotional content that is closely associated with depressive mood, interventions can be tailored to address specific emotional needs and potentially mitigate the risk of depression.

3.3 Capsule network and transformer based emotion prediction

3.3.1 Objective and Architecture

To extract emotional connotations of lyrics we extended the work done by Agarwal et al.(2021) [43], which uses a transformer based approach towards music emotion recognition from lyrics. The model architecture used by them is illustrated in Figure 3.1. We explored a modified architecture based on the ideas presented by Sabour et al., 2017 on capsule networks.

Sabour et al. (2017) [44] proposed that capsule networks are closer to human cognition compared to traditional convolutional neural networks (CNNs) because they capture hierarchical relationships between visual features and employ a dynamic routing algorithm. Capsule networks use capsules, which represent entity or part-level information, capturing properties such as pose and attributes. The dynamic routing mechanism allows information to flow between capsules based on their agreement, resembling iterative feedback processes in the human visual system. These characteristics enable capsule networks to better model the way humans perceive and understand objects based on their parts and spatial relationships.

We hypothesized that similar logic could be applied to language cognition and that semantic relations could be more efficiently learned from representations generated by transformer layers using novel capsule networks.

In essence we wanted to investigate the efficacy of a network that combines the power of the transformer and capsule network in recognizing music emotion using lyrics and comparing the thus obtained results with only transformer-based approach.

The modified architecture used in this study is illustrated in Figure 3.2

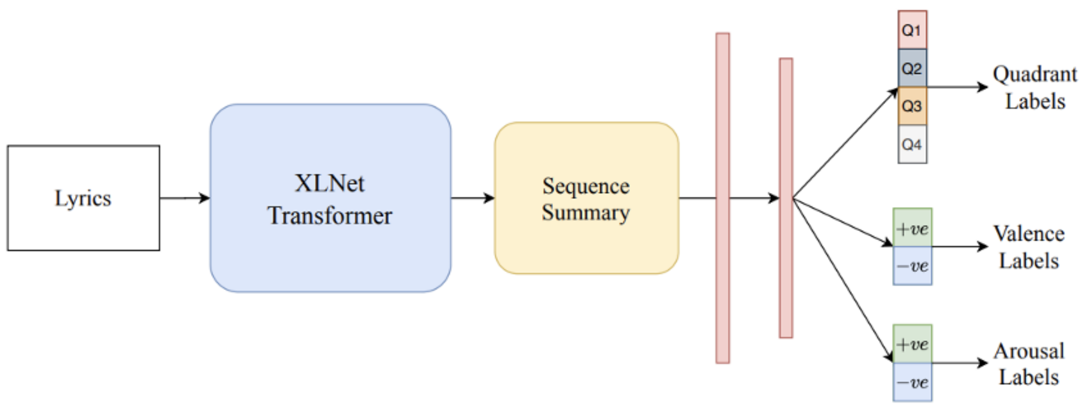

Figure 3.1: Model Overview - Agarwal et. al. (2021)

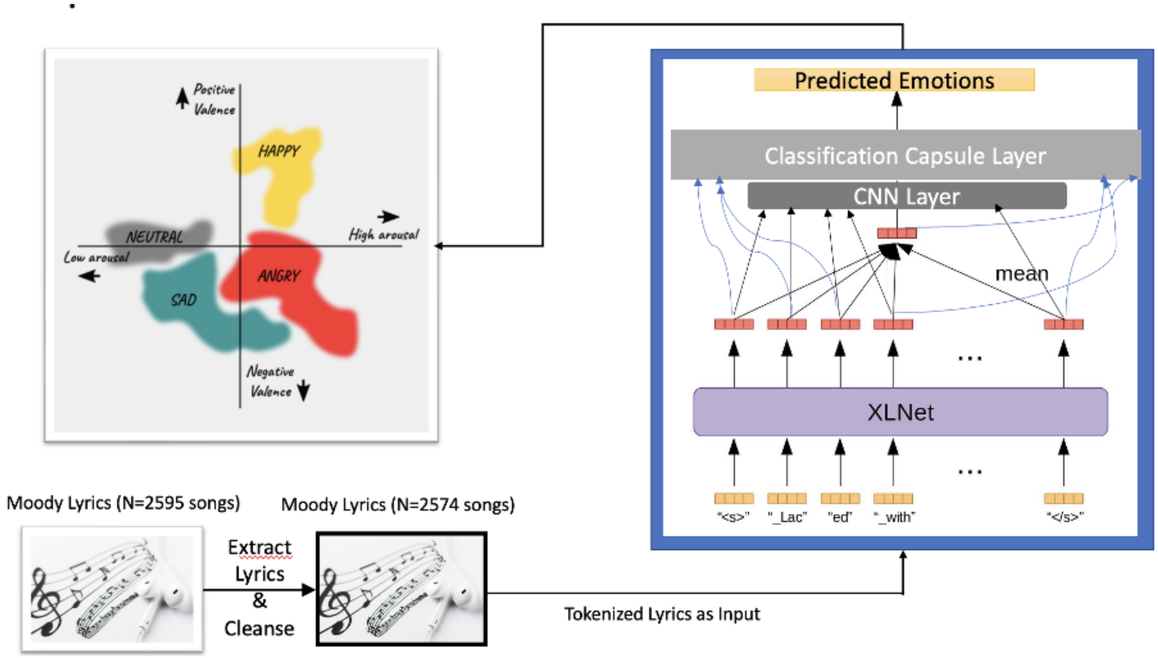

Figure 3.2: Model Overview - Capsule network

3.3.2 Dataset

In our study, we utilized the MoodyLyrics dataset, developed by Çano and Morisio, to assess the performance of our modified model. This dataset consists of 2595 songs with categorized emotions, namely happy (Q1), anger (Q2), sad (Q3), and relaxed (Q4). To determine the emotional values of the lyrics, the authors created a combined lexicon by integrating existing lexicons such as ANEW (Affective Norm of English Words), WordNet, and WordNet-Affect. Valence and arousal values were assigned to each word present in the lyrics, and aggregated scores were calculated and normalized within the range of [-1, 1]. By setting a threshold for valence and arousal, the songs were categorized into specific emotions based on the quadrant in the Valence Arousal plane. The distribution of the songs in various quadrants is given in table 3.1

Table 3.1: Class Distribution

Mood	Songs
Happy	819
Angry	575
Sad	604
Relaxed	597

3.3.3 Results

For evaluating the effectiveness of our proposed model, we use accuracy as the metric of comparison. We use an average over multiple splits and the highest accuracy achieved across folds. Our hybrid model matches up to the existing model with an average accuracy of 93.5% across 5 folds. The accuracy went as high as 96% in one of the folds. The per class accuracy is illustrated in Figure 3.3. The correct classifications were highest for happy (98%) and lowest for sad (93%) in this fold which is representative of other folds too. The misclassifications for MoodyLyrics were predominantly along the Valence axis which is also typical in musical feature-based emotion recognition. This suggests that a hybrid model that combines sequential syntactical processing and hierarchical semantic processing closely emulates human judgment of emotions. We therefore decided to use this model for extracting emotional content from lyrics for the main study.

3.4 Diction: Semantic theme extraction

Diction software is a powerful tool that goes beyond traditional linguistic analysis by providing insights into the underlying semantic themes of a text. In addition to analyzing surface-level

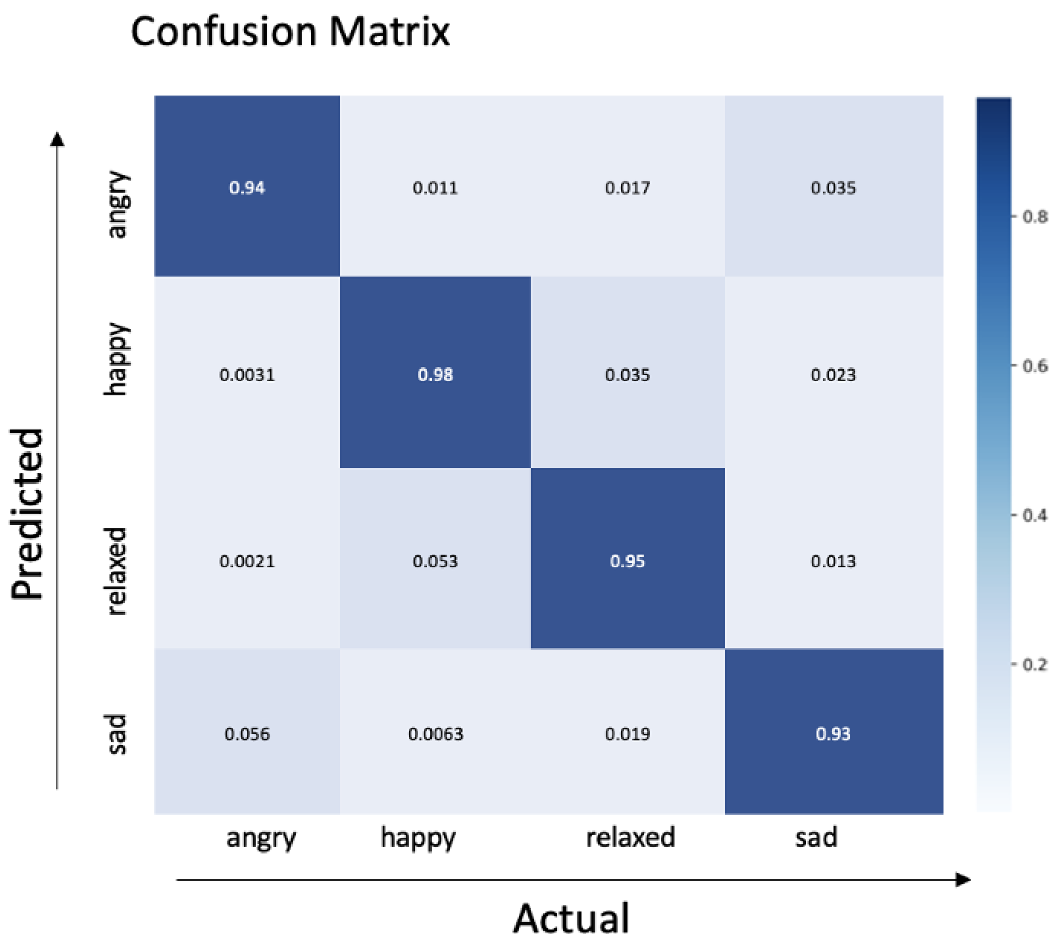

Figure 3.3: Confusion Matrix

linguistic features, diction software has the capability to identify and extract deeper meaning and semantic patterns from written text. The software generated representational scores for the text based on five semantic features (Activity, Optimism, Certainty, Realism, and Commonality), and 35 sub-features This advanced feature of diction software is particularly valuable in various fields such as literature analysis, social sciences, and text mining. By examining the semantic themes of a text, researchers and analysts can gain a deeper understanding of the underlying ideas, emotions, and concepts conveyed within the text. The software employs sophisticated algorithms and natural language processing techniques to identify and categorize the semantic themes present in a given text. These themes can range from broad concepts like love, loss, or power, to more specific topics relevant to the domain of analysis. By extracting the semantic themes of a text, diction software allows researchers to uncover hidden patterns and associations that may not be immediately apparent. It enables them to explore the underlying meanings and sentiments expressed in the text, which can provide valuable insights for further analysis and interpretation. The ability to identify semantic themes is particularly useful in fields such as sentiment analysis, where understanding the emotional tone and connotations of a text is crucial. By uncovering the underlying semantic themes, diction software can contribute to a more nuanced understanding of the sentiment expressed in a text, going beyond simple positive or negative classifications. Overall, the feature of identifying underlying semantic themes in diction software enhances the depth of analysis and interpretation of written text. It enables researchers, analysts, and practitioners to delve into the rich layers of meaning present in a text, facilitating more comprehensive and insightful research in a variety of domains.

3.5 Methodology

3.5.1 Dataset

Details on data collection, processing, and analysis are described below.

3.5.1.1 Data Collection

The study entailed an online survey in which Last.fm group members on social media platforms such as Reddit and Facebook were invited to participate. To be included, participants were required to have actively used Last.fm for at least one year. The survey requested participants to disclose their Last.fm usernames and demographics, and to provide consent to access their Last.fm music history. Standard scales were employed to measure mental wellbeing, musical engagement strategies, and personality traits.

3.5.2 Participants

The study enrolled 541 participants (Mean Age = 25.4, SD = 7.3), of which 444 were male, 82 were female, and 15 identified as other. Most participants were from the United States (30%) and the United Kingdom (10%), while all other countries accounted for less than 5% of the total participants.

3.5.2.1 Measure of depression risk

To assess mental well-being, the study utilized the Kessler's Psychological Distress Scale (K10) questionnaire [2], which measures psychological distress with a focus on symptoms of anxiety and depression. Participants scoring 29 or higher on the K10 questionnaire were classified as being in the "At-Risk" group for depression, while those scoring below 20 were classified as being in the "No-Risk" group [3] as they are likely to be well. Out of the total participants, 193 individuals were in the No-Risk group, and 142 were in the At-Risk group.

3.5.2.2 Music Listening History

The study utilized a publicly available API to extract the music listening history of each participant, which included tracks, associated artists, and social tags. Additionally, the study collected the lyrics of the songs listened to by participants using public APIs and publicly available lyrics repositories/websites. While lyrics were not available for all songs in the public domain, on average, lyrics for approximately 70% <exact percentage to be calculated> of the songs in each user's listening history were obtained..

3.5.3 Lyrics Processing

3.5.3.1 Lyrics-Emotion mapping

The study applied a model presented in a previous section to determine the perceived emotion quadrant for each song's lyrics. This resulted in each song being associated with a specific quadrant in the VA space. The study then calculated the percentage prevalence of each quadrant for each user, based on the top 100 most frequently listened to songs.

3.5.3.2 Lyrics-semantic themes mapping

The study used the diction software to analyze the lyrics and identify underlying semantic themes. The software generated representational scores for the text based on five semantic features (Activity, Optimism, Certainty, Realism, and Commonality), along with 35 sub-features that it supports.

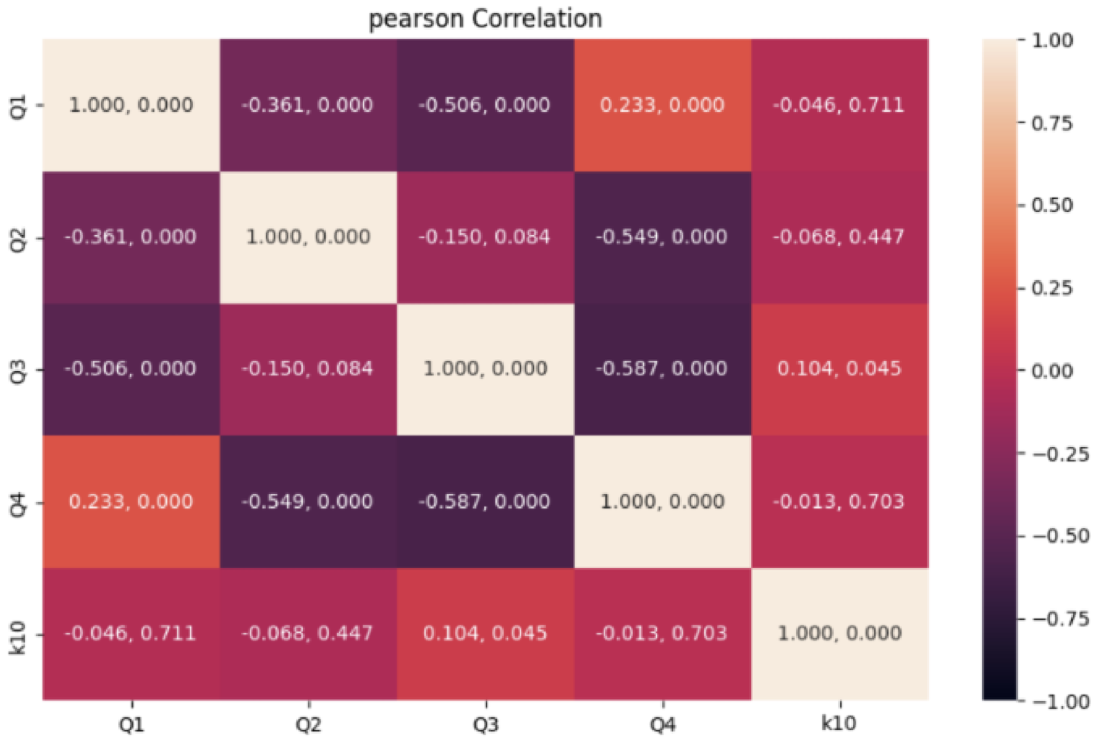

Figure 3.4: Correlations

3.5.4 Results

3.5.4.1 Emotion-based Results

The study found a statistically significant positive correlation ($r=0.104$, $p<0.045$) of K10 scores with Q3 of the VA space, which represents low valence and low energy. Additionally, the study identified significant patterns in inter-quadrant correlations, indicating strong likes and dislikes of listeners for songs in particular quadrants. For instance, individuals who primarily listened to songs in Q3 exhibited a strong aversion towards songs in Q1. Details in Figure 3.4

3.5.4.2 Theme-based Results

The study found pattern in affinities and aversions of users at risk with various semantic themes illustrated in Table 3.2

3.6 Conclusion and Discussion

This study is one of the very few of its kind to examine the association between risk for depression and lyrics of the songs listened by individuals. A clear difference in the music

Table 3.2: correlations to semantic themes

Theme	Pearson correlation	p value
Denial	0.12596992	0.00333646743
Self-reference	0.11067638	0.009988375
Ambivalence	0.1032922	0.01624385377
Tenacity	0.09536584	0.0265493952
Liberation	-0.08754253	0.04181197981
Familiarity	-0.11058438	0.0100507985

listening profiles were observed between the At-Risk group and the No-Risk group, particularly in terms of the lyrics that were perceived as sad (Low valence and Low Arousal). Sadness was significantly more prevalent in the At-Risk group aThe stronger association of the AtRisk group with sadness is in concordance with the past research studies in the field [45] and confirms our hypothesis.

The At-Risk group is attracted to music that reflects and resonates with their internal state. Whether this provides emotional consolation as an adaptive resource or whether it only worsens repetitive negative feelings and fuels rumination, remains an open question. Nonetheless, statistically, such listening style can be seen as a highly predictive factor of psychological distress.

In addition to that, semantic themes like Denial, Self-reference and Ambivalence were also more prevalent in the At-Risk group. Whereas themes like Liberation and Familiarity showed a negative correlation to risk to depression

Chapter 4

Conclusion and Future Work

This thesis attempts to provide valuable insights into the impact of music on mental well-being and the risk of depression, exploring both the ”how” and ”what” aspects of music. The findings of this research align with existing studies in the field while making novel contributions to our understanding of the complex relationship between music and mental health.

HUMS has been shown to possess high validity in the Indian adult population to assess psychological distress and potential risk for depression and other mental disorders. The presence of very low training error and high accuracy of the ML model indicates the existence of a non-linear function that effectively maps the responses from HUMS to the K10 score. Also, this his suggests that the model can learn the function that captures the complexities of mental states, allowing for a nuanced and automated assessment of psychological distress and depression risk. Our contribution is in not just providing evidence to such a function but also proving that an automated way that does not require human intervention is possible for detection of risk to depression.

Existence of such a function also provides additional evidence of the aptness of HUMS as a mental state detector. To add to this, the high predictive power of the machine learning models , especially in the 2 -class problem (as evidenced by significantly high classification accuracy for the moderate to high -risk groups) , further increases the generalizability of HUMS in a global context. Thus, HUMS can be used as a comprehensive and valid instrument to employ in the Indian context as a non -invasive tool to assess mental well -being thereby circumventing the stigma associated with direct assessment and discussion related especially to depression . This has potential implications in a corporate setting wherein detecting internal states and potential risky behavior in employees is vital for constructive intervention

Furthermore, the content of the music, including lyrics and emotional connotations, has been shown to play a crucial role in shaping individuals’ emotional states and vulnerability to depression. The preference for music with sad lyrics and low valence and arousal, as observed in this study, is consistent with prior findings indicating the link between sad music and depressive mood [4] [32]. The association between semantic themes such as Denial, Self-reference, and Ambivalence with depression risk echoes the existing literature on the emotional impact of lyrical content [23][28]. Also, we have provided another automated AI enabled way to automatically detect such vulnerability to depression by sifting through music listening histories of any numberof people in a large population.

Moreover, this thesis contributes to the field by examining the association between risk for depression and lyrics of the songs listened to by individuals, which has received limited attention in previous research. The identification of specific music preferences and semantic themes associated with depression risk adds to the growing body of knowledge and offers new insights into the role of music content in mental health assessment [3] [30].

These findings have practical implications for interventions and recommendations aimed at promoting mental well-being. Understanding the influence of music engagement strategies and content on mental states allows for the development of personalized approaches. By leveraging this knowledge, targeted interventions can be designed to support individuals in managing their mental health and mitigating the risk of depression.

Moving forward, future research should continue to explore the dynamic relationship between music and mental health, considering the cultural and individual differences that influence music preferences and responses. Longitudinal studies can provide a deeper understanding of the adaptive and maladaptive aspects of using music for emotional regulation, while cross-cultural investigations can enhance our understanding of the universal and culturally specific influences of music on mental well-being [31] [16]

In conclusion, this thesis has contributed to the existing body of research by examining the "how" and "what" of music in relation to mental well-being and the risk of depression. The findings support previous studies on the impact of music engagement and content on mental health, while also providing novel insights into the association between lyrics and depression risk. By acknowledging the significance of music in assessing mental states and developing targeted interventions, this research contributes to the advancement of our understanding and the development of effective strategies for promoting mental well-being through the power of music.

Related Publications

1. Agarwal, R., Singh, R., Saarikallio, S., McFerran, K., & Alluri, V. (2019). Mining Mental States using Music Associations. SMM19, Workshop on Speech, Music and Mind 2019.

2. Rajat Agarwal, Ravinder Singh, Petri Toiviainen, Vinoo Alluri. (2021). Music emotion recognition from lyrics using Transformers-Capsule network. 16th International Conference on Music Perception and Cognition

3. Pavani Chowdary, Bhavyajeet Singh, Rajat Agarwal, Vinoo Alluri (Submitted to ISMIR): Lyrically speaking: Exploring the link between Lyrical, Emotions, Themes and depression risk.

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