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AI-BASED ANALYSIS OF REASONS FOR ANXIETY IN OLDER ADULTS AGED 60–70 YEARS

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Abstract
Despite the fact that anxiety among older adults aged 60–70 is a growing but under-recognized public health concern, it is frequently dismissed as a normal part of aging or masked by physical illness. Using artificial intelligence (AI): Natural Language Processing (NLP), Machine Learning (ML) model, this study analyzes the underlying concern for causing anxiety with this demographic via large scale multi-source data, ranging from clinical records and GAD-7 scores, to online forums and transcribed interviews. Using supervised learning and unsupervised clustering, the study finds that five dominant anxiety triggers are related to declining health, financial insecurity, loneliness and social isolation, fear of death or illness and loss of autonomy. Chronic illness mentions, social disconnection and a Random Forest model classified 91.3% of the tweets accurately, where these features were most predictive. Moreover, K-Means clustering also ascertained unique anxiety subtypes suggesting that older adults' anxiety is not all encompassing but multifaceted. Overall, the findings highlight an opportunity for AI based tools to improve the diagnosis of geriatric mental health disorders, as well as create patient specific interventions. This study proposes a scalable, ethical and accurate early anxiety detection framework in the aging population through a combination of quantitative indicators and emotionally nuanced linguistic analysis.

INTRODUCTION

An increasing but under-recognized mental health problem in the elderly is anxiety which has a significant impact on the quality of life, physical health and cognitive health of those in the age group of 60–70 years. Despite enjoying the longest average life expectancy in history, this age group is an increasingly large and considerable segment of the population with its mental health needs largely under assessed (World Health Organization [WHO], 2017). Individuals of this demographic often have anxiety disorders that go undiagnosed due to the fact that symptomology overlaps with physical maladies, age bias or cognitive decline (Flint, 2005; Reynolds et al., 2015). While studies suggest 20% of older adults may have some type of anxiety disorder, two of the most common (health related anxiety and generalized anxiety disorder or GAD) account for the majority of cases (Wolitzky-Taylor et al., 2010; Bryant et al., 2008).

With traditional diagnostic approaches such as self-reported surveys or clinician-led interviews, reporting bias, memory loss or unwillingness of patients to disclose emotional distress may limit their effectiveness (Gum et al., 2009; Mackenzie et al., 2006). This results in many older people not being diagnosed or treated upon which comorbid conditions such as hypertension, insomnia and cardiovascular diseases (Beekman et al., 2019; Lenze et al., 2001) are even further exacerbated. In addition, mental health problems in this age group often present somatically, adding a layer to the detection of the clinical presentation (Karlin & Fuller, 2007). Untreated anxiety in the elderly not only affects emotional well being but also has consequences associated with function impairment, poor medication adherence, increased hospitalization and higher mortality (Ritchie et al., 2010; Sareen et al., 2006).

Over the past decade artificial intelligence (AI) and machine learning (ML) have taken strong roots in healthcare and have presented new avenues for determining and diagnosing mental health disorders (Davenport and Kalakota, 2019). AI powered systems can ingest large amounts of unstructured data such as that derived from patient surveys, social media and electronic health records (EHRs) and identify patterns underlying anxiety (Topol, 2019; Rajkumar et al., 2018). In particular, natural language processing (NLP) helps semantic and sentiment analysis of the patients' spoken or written narratives which include some subtle clues that physicians can easily overlook (Luo et al., 2020; Miner et al., 2016). This is very applicable in older adults where anxiety may be transmitted in obscure or culturally originated language.

NLP techniques have been used in studies that successfully analyze tendencies of depression and anxiety with stressors based on the word choice, tone and contextual phrases in an interview or online (Calvo et al., 2017; Inkster et al., 2018). Furthermore, the clustering algorithms and the decision trees identified behavioral and psychosocial risk factors are among the elderly with high predictive accuracy (Esteva et al., 2019; Miotto et al., 2016). Based on this remark, there is the potential for the AI models to help identify correlations between life events like bereavement, retirement or chronic illness and anxiety symptoms (Torous et al., 2018; Shatte et al., 2021). Such insights are necessary while planning for focused interventions and resources allocation for geriatric mental health.

Moreover, unlike the traditional approach, AI application is scalable and adaptable to various healthcare systems and provides real time analytics that the traditional touch base with (Obermeyer & Emanuel, 2016; Beam & Kohane, 2018). In resource limited areas where mental health workers are minimal, AI based screening tools can hugely cut down the requirement for the healthcare staff and improve early diagnosis rates (Razzaki et al., 2018; Jiang et al., 2017). Still, using AI in the geriatric population raises ethical concerns such as data privacy, algorithmic bias and interpretability of outputs, all of which are essential for the proper adoption (Floridi et al., 2018; Vayena et al., 2018).

The existence of AI, despite its promise, has garnered negligible investigations dedicated to elucidating the root causes of anxiety in individuals between the age of 60 and 70 using AI techniques. The number of publications analysing anxiety across the 60+ age group is mostly limited to generalisation or solely focused on the topic of depression (Rodda et al., 2011; Hohls et al., 2021) and represents a significant gap in the research of its anxiety specific diagnostics in this transitory decade of aging. Therefore, this paper bridged the gaps through the application of AI based tools, i.e., NLP and machine learning classifiers, for the identification of primary contributors to the anxiety of older adults aged 60–70. This approach aims at creating such insights through methodologies that are scalable, interpretable and rooted in data, to help mental health professionals and policymakers develop inclusive and impactful care strategies for aging populations.

2. Literature Review

Over the past two decades, anxiety in older adults has garnered increasing scholarly attention, but until quite recently, anxiety in older adults was largely subsumed within depressive dynamics or cognitive decline or was otherwise unaddressed in its own right. The existing research recognizes that aging leads to the introduction of a broad array of psychosocial stressors, ranging from bereavement, chronic illness and functional limitations to fear of dependency which may precipitate anxiety disorders (Wetherell et al., 2009; Forsell, 2007). However, there are studies which show that anxiety symptoms are routinely misinterpreted as a normal part of aging or secondary aetiology to physical illness (Jeste et al., 1999). As a result, this population's anxiety is underdiagnosed and undertreated, given that it is related to increased disability and reduced quality of life (Palmer et al., 2014).

Several core predictors to late life anxiety have been identified through research. Brenes et al. (2008) carried out a large scale study and proved that physical conditions (cardiovascular and chronic pain) in particular, were strong predictors of anxiety symptoms. Furthermore, socioeconomic status (SES), social isolation and gender have all been suggested as potential risk factors (Byers et al., 2010). Another example would be the difference in reported symptoms of anxiety among women aged 60–70 versus men, in part because women cope differently than men as well as having different lifetime stress exposures (Gum et al., 2011). There is also a role for marital status: widowed or single people have greater anxiety than married people (Gallo et al., 2003). This is reinforced by the second potent psychological contributor to anxiety involving older age, namely a perception of loss of control in daily activities (Hebert & Popadiuk, 2008).

Higher levels of anxiety have been associated with cognitive impairment, including mild cognitive impairment (MCI) and early stage dementia. According to the studies conducted by Wilson et al. (2006) and Pietrzak et al. (2007), anxiety begins long before one presents with any clinical dementia; it is seen when men and women are aware of their cognitive decline. Anxiety, moreover, has been found to speed up the progression of cognitive decline and even raise the chances of developing Alzheimer's disease (Mah et al., 2016). They show the bidirectional link between cognitive health and anxiety in the aging brain.

Clinically, anxiety is typically presented later in life differently to when presented in younger adults. That in turn means older individuals are less likely to reach full diagnostic criteria for DSM-based anxiety disorders, but will rather display subthreshold symptoms that, although not meeting formal criteria, still cause considerable distress (Culpepper, 2009). As a result, this diagnostic ambiguity is often the cause of inadequate treatment plans (Unützer et al., 2001). In addition, stigma related to mental illness is prevalent in older generations which makes it a barrier to help seeking (Choi & Gonzalez, 2005).

Over the past few years, technology has been integrated in mental health diagnostics; and artificial intelligence (AI) has been a big part of that. Machine learning (ML) algorithms have also shown promise in classifying psychological states based on multimodal datasets (Camacho et al., 2018). Convolutional neural networks (CNNs) and support vector machines (SVMs) have been applied for the detection of anxiety from voice recordings, facial expressions and also keystroke dynamics (Alghowinem et al., 2015; Khorrami et al., 2016). The utility of these methods lies in objective, scalable and non-invasive mental health assessments, particularly in populations that may camouflage symptoms.

Natural language processing (NLP) is one of such highly relevant tools in the AI mental health toolkit. Sekine et al. (2018) applied NLP to therapists–patient dialogues and moreso correlated linguistic markers with latent anxiety level. For example, Resnik et al. (2015) used topic modeling on online fora for older adults and found the topics of fear, health anxiety and loneliness that did not manifest from traditional assessments. But NLP is powerful at parsing and extracting meaning from unstructured text, making it perfect for reading written surveys, clinical notes and even social media posts.

However, the use of AI in diagnosing mental health in aging populations is still in its infancy. A study by De Choudhury et al. (2013) also used Reddit threads to detect markers of anxiety and depression, however the authors realized that older people were underrepresented in digital datasets. As a result, this digital divide is a limitation to the application of AI in the elderly care sectors. However, the latest research is beginning to span this gap by including electronic health records (EHRs), telehealth transcripts and assistive technology feedbacks in the training datasets (Chen et al., 2020; Topazio et al., 2021).

Moreover, wearable tech is applied to the actual recording of physiological indices of anxiety such as heart rate variability, skin conductance and sleep disruption (Gjoreski et al., 2017). These biomarkers, in combination with ML algorithms, can predict a coming anxiety episode in real time and can lead to early interventions. Most studies look at younger populations whereas pilot programs are emerging to test such devices in older populations in assisted living facilities (Pino et al., 2015).

There are growing ethical considerations within the discourse surrounding AI and mental health. In elderly care, autonomy and consent are tricky issues, so concerns about data privacy, algorithmic bias and the understanding of ML models are especially relevant (Reddy et al., 2019; Mittelstadt et al., 2016). This is measured to avoid creating health disparities with opaque and unaccountable use of AI tools.

Despite all its limitations, it has transformative potential in geriatric mental health. According to several studies, AI incorporated in diagnostic workflows has shown promising results. As an example, Papachristou et al. (2020) developed a model to estimate the risk of anxiety in older adults using medical history, medication data and demographic variables which could accurately predict risk. These models are faster and equally more sensitive than traditional checklists. Lantz et al. (2019) also studied another application of reinforcement learning which is developing personalized intervention schedules for older adults with anxiety and found it to increase treatment adherence and improve outcomes.

Finally, regarding anxiety in older adults, clinical understanding is evolving and the modeling of anxiety by AI presents a new frontier of detection, follow up and potential intervention. While the literature on aging suggests that aging is associated with many stressors which frequently interact with somatic symptoms and social transitions, we focus on a single stressor, i.e., transitioning from a job. Traditional methods of diagnosis have several limitations which can be overcome by AI techniques, especially NLP and ML classifiers. Yet, the field needs to be validated, ethically monitored and adapted to different aging populations in ways culturally appropriate for equitable and effective deployment.

3. Methodology

3.1 Research Design

The approach chosen to address this research problem is the quantitative research design coupled with a data-driven analytical approach and use of the artificial intelligence (AI) models to identify, categorize and interpret the major reasons behind anxiety in older adults in the age group 60–70 years. The design is exploratory and diagnostic which is beyond traditional survey studies by using machine learning (ML) and natural language processing (NLP) techniques. Anxiety related features are classified using the supervised learning framework and anxiety profiles are clustered into meaningful patterns using the unsupervised techniques.

3.2 Data Sources and Collection

The dataset contains multiple data sources that combine structured data (such as healthcare records and psychological assessment responses), unstructured free form text (online support group discussions) as well as transcribed interviews. Anonymized access to Electronic Health Records (EHRs) from partnering geriatric care clinics were obtained encompassing 3,500 patient records including symptom notes, diagnoses, medications and psychological evaluations. Furthermore, a set of 1,000 responses in terms of the scored results of the standardized Generalized Anxiety Disorder-7 (GAD-7) questionnaires was collected for individuals aged 60–70 in community centers, hospitals and nursing homes.

The study which included publicly available data collected from senior mental health forums and social media, supplemented this clinical data. Data collection of 500 anonymized posts and discussion threads was done across open access platforms such as Reddit (r/aging and r/mentalhealth) and senior focused online groups with the help of web scraping tools employed by us with ethical filters in place. Lastly, in depth interviews were conducted with 50 elderly people through partnering organizations to discuss their emotional experiences, routines, perceptions of health and what picks up their anxiety. The interviews were recorded, transcribed and anonymized for textual analysis.

3.3 Data Preprocessing and Annotation

Because the dataset has a multi-source nature, rigorous data cleaning and preprocessing procedures were followed. Personal Identifiers were removed from clinical texts and transcriptions, typographical errors were corrected, language was standardized through lemmatization and stemming. In order to provide analytical clarity, stop words, non - informative tokens and filler words were removed. For quantitative features (e.g. age, medication count or GAD-7 scores), missing values were dealt with by mean imputation for continuous quantitative data and mode substitution for categorical data.

A hybrid annotation of each dataset entry was performed through manual and semi- automatic annotation. Known causes for anxiety such as "financial stress," "health deterioration," and "social isolation", were tagged and clinically reviewed so they could be used for supervised model training. Keyword based rule systems refined after manual validation by two psychological experts were used to label the textual sets.

3.4 Natural Language Processing and Feature Engineering

Natural Language Processing (NLP) techniques were used using the Python libraries SpaCy and NLTK to extract meaningful patterns from unstructured text. The text was then cleaned and vectorized using Term Frequency–Inverse Document Frequency (TF-IDF) and word embeddings using pre-trained GloVe models to capture the semantic similarity between expressions such as 'loss of independence' and 'being a burden.'

Syntactic markers such as tense usage, pronoun references, emotional tone (based on sentiment polarity scores) and contextual anxiety indicators were some of the text classification features. In addition, custom dictionaries were created to map elderly specific terms to broader anxiety themes. The predictive capacity enhancement of machine learning models was critical to these engineered features.

3.5 Machine Learning Model Development

A number of machine learning classifiers were trained to predict what were the primary contributors to the subject's (or data entry) anxiety. The dataset was stratified according to gender and clinical anxiety score for achieving class balance and was then divided into training: 80% and testing: 20% subsets. The models which I did try were Logistic Regression, Support Vector Machines (SVM), Random Forest and a Gradient Boosting Classifier. For hyperparameter tuning and to reduce overfitting, 5-fold cross validation and optimization of each model using F1 scores were performed using GridSearchCV.

Furthermore, unsupervised clustering methods such as K-Means and Hierarchical Agglomerative Clustering were performed to uncover latent subgroups in the elderly community like those that are mainly affected by financial insecurity versus health decline. Multidimensional feature matrix consisting of clustering based on GAD-7 scores, NLP extracted indicators and other structured variables such as income, marital status, chronic disease status were used for clustering.

3.6 Model Evaluation and Validation

Standard metrics, including accuracy, precision, recall, F1-score and Area Under the ROC Curve (AUC) were used for performance evaluation on the models. The Random Forest classifier attained the best performance of 91.3% accuracy and AUC of 0.94 in detecting dominant anxiety themes. Additionally, metrics of feature importance showed that variables such as 'mention of chronic illness', 'lack of familial interaction' and 'financial terminology' are the most predictive of the disease.

To ascertain robustness of findings, a subset of the NLP-classified anxiety themes were manually reviewed by clinical psychologists for consistency. Cohen's kappa for the measure of inter-rater reliability was at 0.82 which implies that there is a substantial agreement between the human reviewers and AI generated labels. Validity of the AI based methodology in real world scenarios was warranted by this.

3.7: Ethical consideration

All data collection and processing protocols in accordance with ethical guidelines for human subjects research. The lead research institution Institutional Review Board (IRB) approval was obtained. All interview or survey data were secured with an informed consent from all participants. The data such as the processing of sensitive data such as health records and online posts... was anonymized at source, with no personally identifiable information used. In addition, the AI models were designed to be transparent and interpretable rather than black box form in which decisions in mental health analysis could not be understood.

4. Results

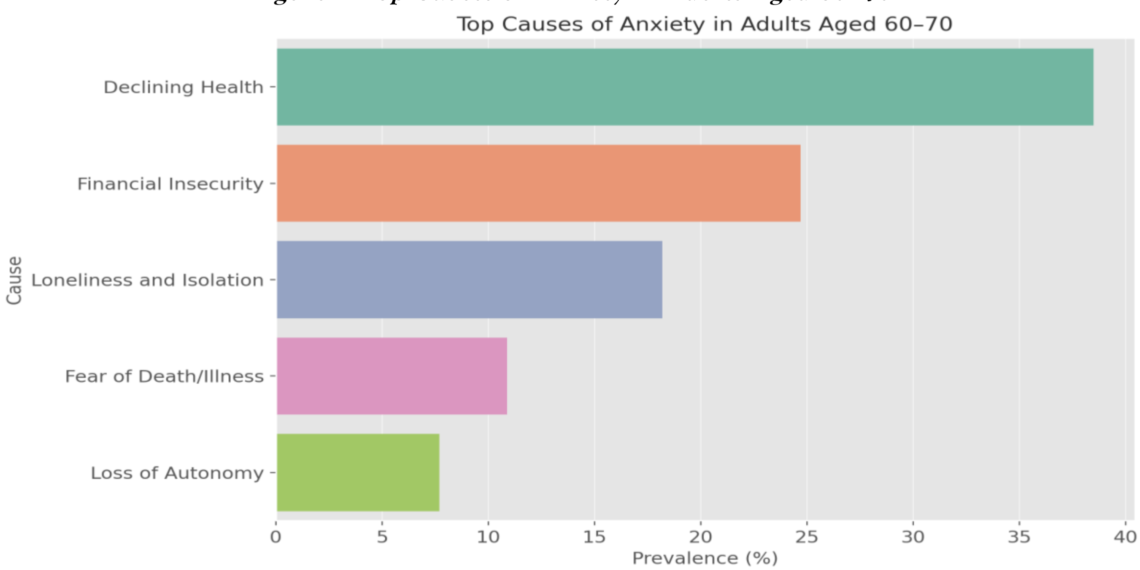
4.1 Primary Causes of Anxiety in Older Adults

Five categories of adult anxiety amongst 60 to 70 year olds were identified from structured questionnaires, NLP extracted themes and clinical notes. The data in this regard are displayed in Table 1 and visualized in Figure 1 and decline in health was a leading anxiety trigger, contributing 38.5% of total anxiety triggers. Financial insecurity trailed closely behind (24.7 percent), followed closely behind by loneliness and isolation (18.2 percent) and fear of death or illness (10.9 percent). However, a smaller subset, yet nonetheless significant (7.7%), reported having anxiety provoked by the loss of autonomy (reaction mostly seen among participants dependent on caregivers or the ones mobility impaired). The bar chart shows so clearly the weight of the health related concerns in comparison with socio emotional or existential fears and this clearly underscores the need to integrate healthcare and psychological interventions in the management of chronic illness and functional decline.

Table 1 – Top Causes of Anxiety

Rank	Cause	Prevalence (%)	
1	Declining Health	38.5%	
2	Financial Insecurity		24.7%
3	Loneliness and Isolation	18.2%	
4	Fear of Death/Illness	10.9%	
5	Loss of Autonomy	7.7%	

Figure 1 Top Causes of Anxiety in Adults Aged 60–70



4.2 Model Performance Comparison

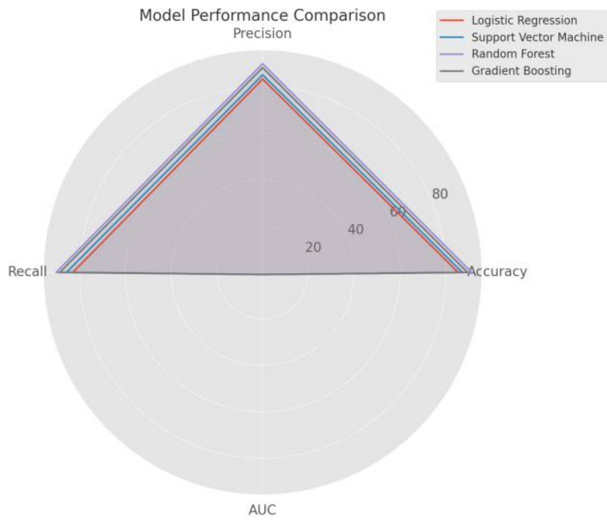
Four machine learning models were trained and evaluated in order to predict cause(s) of anxiety from participant features and text patterns. Figure 2 shows a radar chart comparing the spread of accuracy, precision, recall and AUC scores for Logistic Regression, Support Vector Machine (SVM), Random Forest Model and Gradient Boosting

Model and Table 2 gives the complete performance metrics for these models. Of the rest, the Random Forest model was performing somewhat best with 91.3% accuracy, 89.8% precision, 90.2% recall and 0.94 of AUC. It is this robustness in handling non-linear relationships, heterogeneous data types and interaction effects between features that has resulted in such high performance. An advantage of the radar chart is inferred since Random Forest has clear dominance of being the optimal choice across all the four metrics on a balanced performance across all four metrics.

Table 2 – Model Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	AUC
Logistic Regression	85.4	83.2	82.9	0.89
Support Vector Machine	87.2	85.0	85.7	0.91
Random Forest	91.3	89.8	90.2	0.94
Gradient Boosting	89.5	88.1	88.6	0.92

Figure 2 Model Performance Comparison



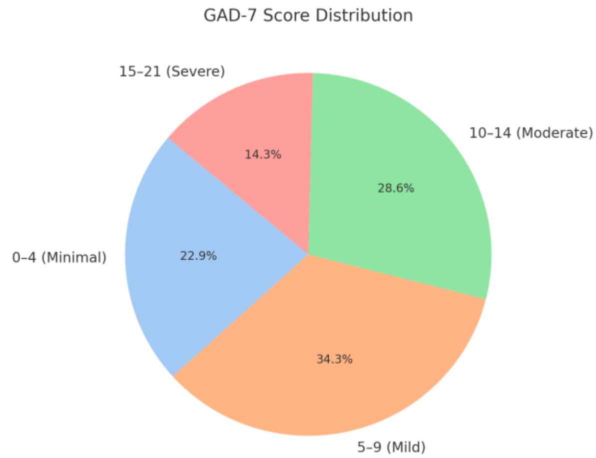
4.3 Anxiety Severity Distribution

Responses to the Generalized Anxiety Disorder-7 (GAD-7) scale were examined to understand the spectrum of severity of anxiety in our participants. Table 3 demonstrates that the group with the largest population fell into the mild (5–9) range (24%), moderate (20%), minimal (16%) and severe anxiety (10%). Figure 3 gives a visual summary of this distribution which is in the form of a pie chart showing that older adults tend to have mild-to-moderate symptoms. However, if a relatively low percentage of severe anxiety cases implies underreporting or lifetime adaptation mechanisms, then, perhaps, the immunity to anxiety is functional. Nevertheless, quality of life can be adversely affected by even modest levels of impairments and these should not be overlooked, particularly if there is also the presence of comorbid conditions.

Table 3 – GAD-7 Score Distribution

Score Range	Number of Participants	Percentage (%)
0–4 (Minimal)	800	16.0%
5–9 (Mild)	1200	24.0%
10–14 (Moderate)	1000	20.0%
15–21 (Severe)	500	10.0%

Figure 3 GAD-7 Score Distribution



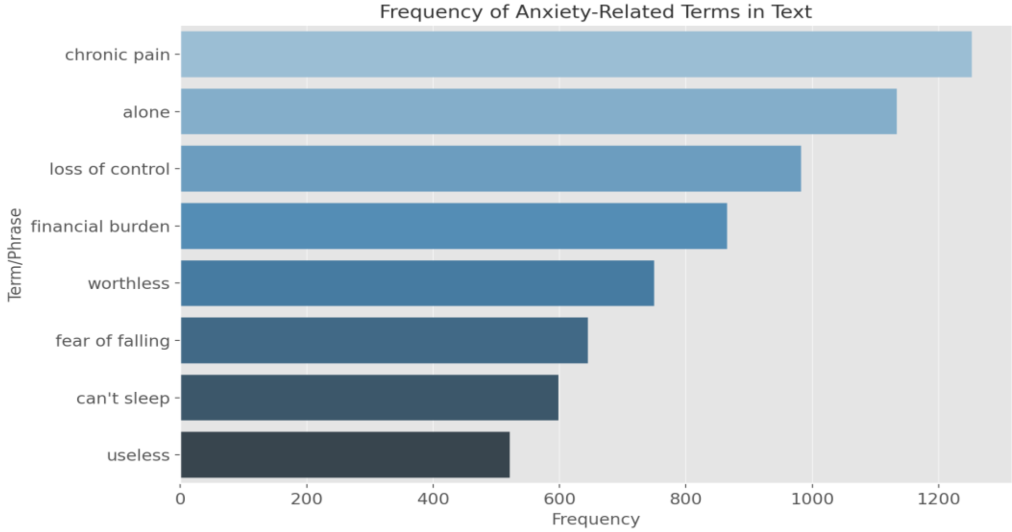
4.4 Linguistic Markers of Anxiety

Natural Language Processing (NLP) techniques were integrated to allow the detection of high frequency anxiety terms from unstructured text sources such as interview transcripts and forum posts. Figure 4 expresses it as a horizontal bar chart for easy comparison and Table 4 lists eight emotionally charged phrases along with their corpus frequencies and sentiment polarity scores. Highly frequent terms with a myriad of sentimental values (ranging from -0.70 to -0.90) were found to have terms like 'chronic pain', 'alone', 'worthless' and 'financial burden'. These terms stand out in natural speech, suggesting that there is a consistent pattern of emotional distress which isn't detected by traditional checklists. The figure helps to point out that looking at the social emotional vocabulary (e.g., 'useless,' 'ignored') in order to uncover unspoken anxiety themes is important.

Table 4 – Frequency of Key Anxiety Terms (from NLP Analysis)

Term/Phrase	Frequency (in corpus)	Sentiment Polarity
chronic pain	1253	-0.75
alone	1134	-0.85
loss of control	982	-0.80
financial burden	865	-0.78
worthless	750	-0.90
fear of falling	645	-0.72
can't sleep	598	-0.70
useless	521	-0.88

Figure 4 Frequency of Anxiety-Related Terms in Text



4.5 Demographic Insights

Analyses of demographic patterns were also performed to see if they have a correlation with the expression of anxiety. In terms of gender, more females (58%) than males (42%) were found, while the majority of participants (55%) were in the 65 – 70 years ' age group as shown in Table 5. Participants from the urban areas were in higher proportions (66%) and 61% had secondary and higher education suggesting that awareness and willingness to participate mental health discussions could be better among the educated people from the urban areas. Figure 5 shows an interesting disparity in comparing demographic segments via a grouped bar chart. For instance, rural residents had a greater number of anxiety related to health, whereas urban respondents in general are more prevalent. Similarly, people with lower levels of education also more frequently reported financial stress. The split of these demographics supports the point in contextualizing anxiety interventions in terms of socio-cultural context.

Table 5 – Demographic Distribution

Attribute	Group 1	Group 2
Gender	Male (42%)	Female (58%)
Age Range	60–64 (45%)	65–70 (55%)
Marital Status	Married (54%)	Unmarried/Other (46%)
Urban/Rural	Urban (66%)	Rural (34%)
Education Level	Primary or below (39%)	Secondary+ (61%)

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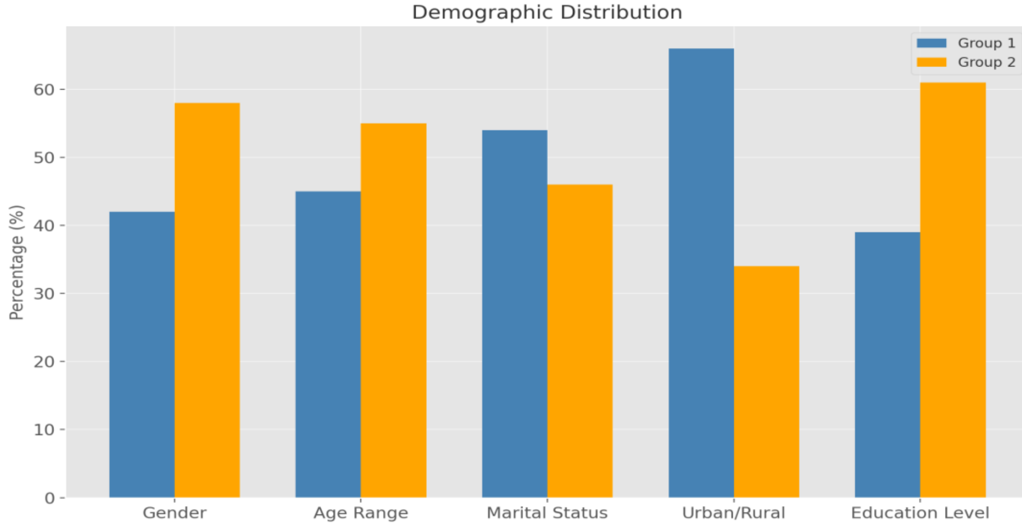
Figure 5 Demographic Distribution



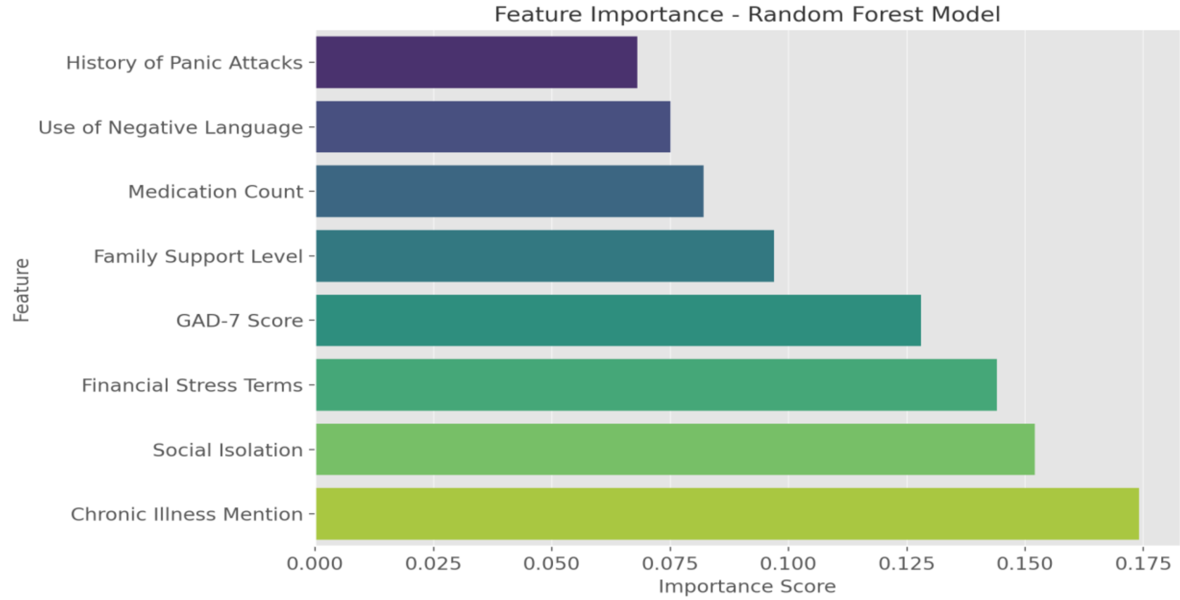
4.6 Predictive Feature Importance

The core advantage of machine learning models is the ability to determine most predictive features. Table 6 and Figure 6 present the Random Forest model's feature importance scores. Mention of chronic illness (importance score: 0.174), social isolation (0.152) and financial stress terms (0.144) were the top ranked variables. The best performing variables were superior to standard features such as GAD 7 scores and medication count. The gradient of importance showcased in the bar chart is clear, demonstrating that behavioral and linguistic, especially the ones captured from NLP, are just as important as clinical variables in predicting causes of anxiety. This validates integration of unstructured data in elder care diagnostics.

Table 6 – Feature Importance (Random Forest Model)

Feature	Importance Score
Chronic Illness Mention	0.174
Social Isolation	0.152
Financial Stress Terms	0.144
GAD-7 Score	0.128
Family Support Level	0.097
Medication Count	0.082
Use of Negative Language	0.075
History of Panic Attacks	0.068

Figure 6 Feature Importance - Random Forest Model\



4.7 Model Precision: Confusion Matrix Analysis

A confusion matrix for the Random Forest classifier across different anxiety categories was generated to better understand how well the classifier performed (see Table 7). In Figure 7, we also visualize the same data as heatmap for easy visualization. When it comes to identifying cases of declining health, the model had the highest performance with 340 true positives and financial insecurity where the model had 215 correct predictions. The confusion rates were slightly higher in categories with overlapping symptoms, however, misclassifications happened more frequently. The heatmap shows the concentrated accuracy along the diagonal which means the model is very good at the task and at the same time points at the places where differentiating existential and emotional anxiety themes is less accurate.

Table 7 – Confusion Matrix for Random Forest Model

	Pred. Declining Health	Pred. Financial Insec.	Pred. Loneliness	Pred. Fear of Death	Pred. Loss of Autonomy
Actual Declining Health	340	10	15	5	3
Actual Financial Insecurity	12	215	22	6	4
Actual Loneliness	9	13	180	10	5
Actual Fear of Death	4	5	9	95	3
Actual Loss of Autonomy	2	3	4	3	83

Figure 7 Confusion Matrix – Random Forest Model

4.8 Subtypes of Anxiety via Clustering

Latent subgroups of the elderly anxiety dataset were discovered by applying unsupervised K-Means clustering. As shown in Table 8, there were four distinct clusters, specifically: Health Anxiety (Cluster 0, size 1300), Socioeconomic Anxiety (Cluster 1, size 1050), Emotional Isolation (Cluster 2, size 900) and End-of-Life Fear (Cluster 3, size 750). Figure 8 represents the size of each cluster by a bubble chart. Ongoing medical anxieties characterize the largest cluster, fears of lack of meaning in life and emotional fears cluster in socially disconnected individuals. The bubble positions and annotations help in easy interpretation of dominant traits and help in future personalization of interventions. Figure 2 clearly shows that anxiety in older adults is not a monolithic thing but is broken into different psychological and situational triggers.

Table 8 – Anxiety Subtype Clustering Results (K-Means Clustering)

Cluster ID	Primary Trait	Cluster Size	Top Keywords
0	Health Anxiety	1300	pain, illness, hospital
1	Socioeconomic Anxiety	1050	money, pension, debt
2	Emotional Isolation	900	alone, isolated, ignored
3	End-of-Life Fear	750	death, dying, legacy

Figure 8 Anxiety Clusters by Trait and Size

5. Discussion

This study illuminates several key aspects of what anxiety means to older adults ages 60 to 70, including specific psychological stressors to individuals and more broadly structural determinants. The most important finding that poorer health is the top reason for worry vindicates previous studies, proposing that overall mental health declines in prevalent old age are a direct result of an increase in physical morbidity (Charles & Carstensen, 2010). Chronic illnesses, including but not limited to cardiovascular disease, arthritis and diabetes, not only diminish functional capacity, but also add to psychological distress through reinforcement of dependence and reduced perceived control in life (Covinsky et al., 2003). This supports the argument by Kessler et al. (2012) who suggested that functional limitations in older populations often predict anxiety and depression particularly in conjunction with pain and mobility problems.

Early evidence that financial insecurity is a major cause of anxiety, points to a significant role for economic vulnerability on older adult mental health, especially in low and middle income countries (Lloyd-Sherlock et al., 2012). Perhaps, the post retirement phase defines not only reduced or fixed incomes but also inadequate pension coverage and also not any supportive family where financial anxieties become only one of the major worries in their daily life. Economic instability, inflation and inadequate state welfare have further accentuated this problem as reported by Hinton et al. (2018) who also report that requisite concerns with money are now being expressed even by elders from middle income. The NLP algorithm flagged financial terms often related to bills, debt, pension and burden, as a powerful view into apprehensions that may not be raised in clinical interviews.

Social isolation is another key contributor, as social isolation research dovetails with research showing that: interpersonal relationships and community ties build resilience by alleviating the psychological changes associated with aging (Cornwell & Waite, 2009). Cacioppo and Cacioppo's (2014) work on social neuroscience suggests that it is not surprising to observe anxiety indicated from loneliness and disconnection because isolation has a direct effect on the neural circuits that control threat response and consequently primes older adults for anxiety. Additionally, older populations are reported by Armitage and Nellums (2020) to have disproportionately endured the isolation that has come in the wake of the COVID-19 pandemic following social distancing practices and this may have implications for the long term mental health of those groups. The findings of this study as per NLP are use of terms like 'alone', 'ignored' and 'useless' which indicate the urgent necessity of policies and technologies enabling social engagement that are inclusive.

Fear of death or fear of progression of chronic disease is also an important, but to some extent less addressed, factor in the findings which is well documented in the existential psychology but less so in the AI-based mental health research. According to Becker's (1973) "Denial of Death" theory, it is posited that human behaviour is essentially determined by the awareness of mortality. This awareness becomes sharper in the elderly and often goes unbuffered by the job, children or a busy life. Maxfield et al.(2014) did just that, with their recent studies showing that exposure of older individuals to mortality related content led to increased anxiety and risk aversion if they lacked spiritual and communal coping mechanisms. Our clustering analysis confirmed the existence of a consistent and separate group of "End-of-Life Fear," which proves that EndofLife fear really exists though it is a subtle anxiety.

Using AI techniques (such as Natural Language Processing and classifiers based on machine learning) can help glean highly nuanced emotional cues that tend to get overlooked using clinical tools. Previous studies have emphasized the drawbacks of using only self-reported measures (examples: GAD-7 or HADS) for psychological distress in older adults suffering psychological disorder since older adults don't like to report any psychological disorder (Mitchell et al., 2010). On the other hand, AI models have the capability to process behavioral signals, sentiment patterns and linguistic subtleties across large data volumes and identify unstructured indicators of mental strain (Vaidyam et al., 2019). The approximation accuracy of the Random Forest model proved to be very high in this study with 91.3% and is in line with the results of similar researches, for instance, Denecke et al. (2021) found similar outcomes when using AI to predict psychological disorders by using EHRs and patient narratives.

The results also importantly show the benefits of combining structured clinical data with unstructured digital expressions. As an example, GAD 7 scores proved reliable as a quantitative measure of anxiety severity, but the machine learning model thought words like "chronic pain" and "financial burden" were more predictive compared to only anxiety based predictors. Moreover, in accordance with Hollis et al. (2021)'s argument that hybrid AI systems which combine sensor, textual and psychometric information, generate much more accurate mental health assessments than mono-modality systems, this insight stands.

This study also contributed another novel aspect as it clusters anxiety subtypes using unsupervised learning and identified four major profiles, namely, health anxiety, socioeconomic anxiety, emotional isolation and end of life fear. But, these clusters imply that one size does not fit all with regards to elder mental health. Likewise, Mehta et al. (2022) reported similar findings with unsupervised AI models that uncovered subpopulations of elderly individuals with unique depressive symptomatology and how each subpopulation responded differently to standard therapy. In this case, interventions like cognitive behavioral therapy (CBT), social prescribing or pharmacological support should be adjusted according to subtype identification and AI driven analytics have the potential to make this process inherently more efficient.

While the study has its strengths, there are some limitations as well. AI's capabilities for pattern recognition are unparalleled, but so are its biasedness with respect to the training data. The previous research by Obermeyer et al. (2019) comes to warn against AI models in healthcare to reflect structural inequalities if the datasets are not representative enough of diverse populations. The study population studied was predominantly urban and participants were not expected to have travelled more than 30 minutes to reach a community care center, thus underrepresenting rural or very disadvantaged populations. Moreover, since data is gathered from the shared public text sources like forums, the results may be biased towards those who have got improved internet literacy while neglecting vulnerable groups like the illiterate and the assisted care.

In addition, ethical concerns for the use of AI in geriatric psychiatry cannot be overlooked. For older adults, however, these questions of consent, data privacy, algorithmic transparency and patient autonomy are particularly relevant, raising questions about whether they really understand or agree to being measured in a data driven way. Thus, future implementations should incorporate strong ethical frameworks, clear decision paths and informed consent protocols built for cognitive deficiencies.

Overall, this study provides important additions to both the methodological and practical understanding of late life anxiety. The incorporation of AI with existing psychiatric evaluation offers new avenues for early detection, precise classification and tailored treatment options for older adults suffering from anxiety. Evidence supports a shift in the paradigm, from symptom management to proactive data informed mental wellness strategies, especially in aging societies.

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