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Diagnosing Death Anxiety with AI in Diabetics and Phobias and Distraught Dreams

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ABSTRACT

Artificial intelligence (AI) offers significant potential for detecting symptoms of death anxiety and improving both diagnostic accuracy and therapeutic strategies. This study seeks to provide healthcare professionals with more efficient tools to manage death anxiety in individuals with diabetes, phobias, and sleep disorders. While mental health concerns have traditionally been explored within social frameworks, AI is increasingly recognized as a valuable resource in psychological care. This paper presents an integrative analysis of the relationship between diabetes, phobias, sleep disturbances, and death anxiety, focusing on research conducted from 2018 to 2023 using Latent Dirichlet Allocation (LDA) thematic modeling. Findings suggest that investigating the overlap of these conditions may offer meaningful insights for future studies. Importantly, AI appears to enhance the early identification and treatment of anxiety, particularly anxiety related to mortality. By analyzing sensor data with AI algorithms, early indicators of anxiety can be detected, allowing timely intervention and improved patient outcomes. The study utilized the Web of Science database, applying search terms such as "diabetes," "phobia," and "sleep disorders." The LDA model revealed hidden semantic structures and calculated co-occurrence metrics to evaluate thematic coherence. Overall, this research highlights AI's critical role in the detection and management of death anxiety and emphasizes the need for continued investigation in this domain.

1. INTRODUCTION

Since the late 21st century, numerous anxiety factors in the field of public health have impacted countries globally [1]. These factors are often associated with death anxiety and negative emotions within communities, posing substantial challenges to public safety. The World Health Organization (WHO) has identified death anxiety as a

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matter of international concern in public health, categorizing it as a Public Health Emergency of International Concern (PHEIC). Among these adverse elements, diabetes, phobia, and sleep disorders are the most prevalent conditions linked to death anxiety, resulting in significant disparities in quality of life [2].

Previous research has indicated that death anxiety is associated with an increased prevalence of mental disorders [3]. Consequently, the study of mental health has progressively garnered significant attention within the scientific community. For instance, an article published in the New England Journal of Medicine predicted a likely occurrence of depression and anxiety among individuals with diabetes. Bolton et al. [4] identified that domestic confinement during the coronavirus pandemic correlated with heightened death anxiety and depression, due to enforced measures that limited social interactions. Depression and anxiety typically co-occur. Nonetheless, there remains a paucity of research exploring the interrelations among death anxiety, phobia, disturbed sleep, and diabetes. This study proposes to examine death anxiety through a literature review and the identification of research hotspots, with and without the integration of artificial intelligence (AI). Additionally, we aim to scrutinize the incorporation of AI technology in mental health research, providing a comprehensive analysis of emerging themes within this domain. Employing the Latent Dirichlet Allocation (LDA) topic model, this AI-LDA research seeks to identify salient topics within a specific corpus of texts, elucidating these topics through distinctive research methodologies.

Artificial intelligence (AI) today offers considerable potential in the field of mental health for the diagnosis and intervention of anxiety disorders, particularly in contexts involving mortality. Recent research has demonstrated that data analysis from sensors and AI algorithms can provide early indicators of anxiety in patients. These markers include alterations in sleep patterns, physical activity, speech patterns, and physical movements. Studies have shown that AI can detect these changes with greater accuracy and speed, enabling healthcare professionals to deliver more effective treatments and interventions to alleviate patient anxiety. Furthermore, AI serves as a pivotal tool in enhancing diagnostic and therapeutic methods for anxiety disorders. Through the application of deep learning algorithms, anxiety-related behavioral and cognitive patterns can be identified in patients, thereby facilitating the development of more personalized and efficacious treatment plans. These tools not only enhance clinicians' understanding of patients' conditions but also improve counseling and support for patients and their families, which is crucial in addressing mortality anxiety [5].

The application of artificial intelligence (AI) in the diagnosis and intervention of mental disorders, particularly death anxiety, has emerged as one of the most significant innovations in the field of mental health. By analyzing data from sensors and behavioral patterns, AI algorithms are capable of early detection of anxiety markers, such as alterations in sleep patterns and physical activity, which may indicate an individual's mental state. Given the emphasis of your research on death anxiety and the utilization of AI in this domain, it is advisable to leverage comprehensive resources such as PubMed, Scopus, and Google Scholar to gather and analyze extensive data and pertinent articles. Additionally, employing more sophisticated AI methodologies, such as deep learning, can facilitate the development of highly effective predictive models for the early detection of death anxiety. Collaborating with multidisciplinary teams of experts can further enhance the progression of your research, fostering novel ideas to refine your research methodologies and outcomes.

A more accurate understanding of mental health can significantly mitigate injuries arising from public health risks and offer valuable guidance for managing similar events in the future. This paper, therefore, will concentrate on three prevalent conditions and associated negative emotions: diabetes, phobia, and sleep disorders. These conditions will be examined within the context of research on negative emotions and the application of artificial intelligence. The primary aim of this review is to predict future research trends by providing an in-depth analysis of AI and Latent Dirichlet Allocation (AI-LDA) in studies focusing on diabetes, phobias, and sleep disorders, with a particular emphasis on the role of death anxiety in the research process.

2. METHODS AND MATERIALS

To identify relevant articles, the primary Web of Science database was systematically searched. The review focused on publications from January 2018 to December 2021, which defined the timeframe for examining research related to death anxiety (T2). The search strategy followed two primary objectives:

In the initial phase, “diabetes” was used as the core keyword. The total number of retrieved articles was recorded, followed by an analysis of the most frequently cited keywords in highly referenced studies. These keywords were then individually combined with “diabetes,” “phobia,” and “sleep disorders” in separate searches. The number of retrieved documents was documented, and the top 7–10 most relevant articles were selected based on relevance and citation frequency.

The second objective focused on identifying thematic connections. Four specific keyword combinations were employed: diabetes and anxiety (D-a), phobia and anxiety (Ph & a), disturbed sleep and depression (DS & D), and death anxiety (DA). For each pair, the number of retrieved articles was recorded to explore their interrelationships.

To uncover latent semantic structures, Latent Dirichlet Allocation (LDA) was employed. LDA treats documents as mixtures of latent topics, with each topic defined by a probability distribution across a set of words. To assess the performance of the LDA model, the coherence score was used as a key metric. This score measures the degree of semantic similarity among word pairs within a topic and normalizes these values between 0 and 1, with higher scores indicating stronger topic coherence.

The LDA model was implemented using the Gensim Python package (version 4.3.1) within a Python 3.9.12 environment. The implementation proceeded as follows:

First, words within each dataset were tokenized, and common bigrams and trigrams were preserved, transforming document titles into text corpora. Common stop words such as “one” and “is” were removed.

The cleaned datasets were then input into the LDA model. The parameter num_topics was varied from 3 to 5 across different iterations, and the resulting topics and their coherence scores were recorded.

Finally, topic sets with the highest coherence scores were selected for further analysis.

3. RESULTS

The findings of the study are initially presented descriptively. The number of annual papers in the field of AI-LDA is shown in Table 1. With the incorporation of AI elements, research on three relatively adaptive emotional disorders has maintained its initial distribution. Research on phobias accounts for the highest number of publications, followed by diabetes, and lastly, disturbed sleep, which has the fewest articles. This trend indicates that research on death anxiety has experienced significant growth, outpacing studies focusing solely on issues such as fear or loneliness [5]. This growth underscores the increasing attention of researchers towards integrating artificial intelligence into past studies in the field of emotions.

Table 1. Number of articles on artificial intelligence and phobia, artificial intelligence and disturbed sleep, artificial intelligence and diabetes (AI-LDA)

Year	Sleep disturbed and AI	Diabetes and AI	Phobia and AI
2018–2019	144	2652	6060
2020–2021	504	6152	11 550
2022.1–2023.3	522	6456	12 000

3.1. AI and Phobia

As illustrated in Table 2, AI technology has been predominantly employed in the diagnosis of mental disorders to analyze the emotional states of specific groups. Additionally, this technology has significantly contributed to the analysis of data collected from sensors [5]. Basic machine learning models, such as random forests, have demonstrated strong predictive power in this research domain (Table 2). The Latent Dirichlet Allocation (LDA) model was utilized to identify topics and key terms in articles related to phobia and artificial intelligence in the context of death anxiety. The relevant articles were then summarized, and the topics were named accordingly.

Table 2. Analysis of mental disorders diagnosis with the help of AI technology

Date	Topic	Keywords	Coherence
2018–2019	Phobia treatment	Disorder, phobia, prognosis, phobia therapy, diagnosis of anxiety	0.564
	Fear detection	Anxiety, B-disorder, pity, individuals	
2020–2021	Fear detection	Anxiety, death, fear, behavior, cognitive behavioral therapy (CBT) , exposure therapy	0.559
	Fear in public	Anxiety, fear, excitement, processing, relaxation techniques, stress management	
2022.1–2023.3	Fear relief	Anxiety, fear-mindfulness meditation	0.544
	Fear detection	Anxiety, depression, fear, and analysis	
	Fear under pandemy	Anxiety, processing	

For instance, during the COVID-19 pandemic, extended societal restrictions led to a noticeable rise in anxiety and phobic reactions across the general population. Consequently, the scope of AI applications in mental health has broadened beyond clinical populations to include the wider public. In one study (8), natural language processing was used to analyze online posts, offering insights into the overall psychological well-being of internet users. AI techniques have also been applied to identify death anxiety through dynamic emotional data, utilizing tools such as facial expression analysis (9), vocal emotion recognition (9, 10), multimodal emotion detection (11, 6), and computational models based on personality traits (10). Moreover, AI has been instrumental in issuing early warnings for individuals at risk of suicidal behavior (4).

In the post-pandemic period (January 2022 to March 2023), anxiety-related research has remained a central focus. Many studies have adopted machine learning methods to manage large-scale datasets and to model population-level mental states in the context of widespread illnesses like COVID-19 (10). These capabilities have significantly advanced the field of anxiety detection, enabling the development of more accurate and realistic diagnostic models (12). Additionally, AI-based interventions have been investigated for reducing death anxiety in elderly populations (13), underscoring AI's growing importance in addressing the psychological challenges of aging societies.

3.2. AI and Disturbed Sleep

Given the widespread occurrence and serious consequences of disturbed sleep, this area represents the most extensive field of research within the AI-LDA framework. Compared to other domains, it encompasses a significantly greater number of studies and thematic topics. When examined through both pre- and post-pandemic lenses, these topics can be categorized into long-term research trajectories and emerging contemporary themes (see Table 3). Since 2018, diagnostic methodologies influenced by artificial intelligence and machine learning algorithms have been increasingly applied. These analyses span various data types, including textual content, figurative expressions, behavioral patterns, and physiological signals (13).

Due to the high diagnostic precision offered by deep learning techniques, recent studies have increasingly prioritized their use. Machine learning is particularly prevalent in sleep-related research because of its strong interpretability. This reverse analytical approach explores the contributing factors to disturbed sleep such as sleep irregularities, psychological stress, and death anxiety using models like random forests to examine their associations with diabetes, phobias, and sleep disorders.

Furthermore, investigations into sleep-related illnesses extend to disorders such as depression (12), neurodegenerative conditions like Parkinson's and Alzheimer's, and even certain types of cancer (13). Some studies have also explored the correlation between fear of nightmares and these medical conditions. AI-based methods are now being utilized to predict disease likelihood based on the emotional states associated with disturbed sleep.

It is noteworthy how death anxiety affects sleep quality and, conversely, how disturbed sleep impacts death anxiety. Death anxiety may cause sleep problems such as sudden wakefulness or disturbed sleep, leading to increased anxiety and mental stress. Conversely, sleep problems can exacerbate death anxiety, creating a vicious cycle. Scientific research and further studies in this field can provide more detailed information and communication strategies. This includes closer examinations of the relationship between death anxiety and disturbed sleep and identifying ways to manage and reduce both of these issues.

Table 3. Analysis of sleep disorder diagnosis with the help of AI technology

Date	Topic	Keyword	Coherence
2018–2019	Adolescent's distressed sleeping	Sleep disturbance, quality of sleep	0.52
	Analysis with twitter	Lack of sleep, sleep disturbance	
	Distressed sleeping related disease	Sleep patterns, sleep hygiene	
	Distressed sleeping detection	Insomnia, nightmares	
2020–2021	Distressed sleeping detection	Detecting insomnia, detecting sleep disorders, detecting sleep disorders	0.48
	Suicide prevention	Mental health intervention, suicide risk assessment , crisis intervention	
	Treatment decisions	Therapeutic interventions, medical management choices, treatment planning	
2022.1-2023.3	Treatment decisions	Student sleep problems, treatment options Drug choices Intervention strategies Clinical guidelines	0.53
	Distressed sleeping of students	Student sleep problems, student sleep problems, sleep problems in students	
	Distressed sleeping related factors	Factors affecting sleep disturbance, effects of sleep disturbance، Sleep-related stressors	
	Distressed sleeping related disease	Sleep disorders-sleep disorders - medical conditions affecting sleep patterns-circadian rhythm disorders Sleep-related respiratory disorders (e.g., sleep apnea) Parasomnia (e.g., nightmares, sleepwalking) Restless legs syndrome Narcolepsy	

3.3. Diabetes and AI

The increasing incidence of diabetes, coupled with therapeutic advances leading to lower mortality rates, has resulted in a global rise in diabetes prevalence. Despite significant strides in diabetes treatment, certain aspects of its management remain ambiguous, highlighting gaps in our understanding of its pathophysiology. Alongside physiological factors, there is growing recognition of the profound impact psychological factors have on the well-being and quality of life of individuals with diabetes. Studies have demonstrated that mood and emotional states, which significantly influence both the incidence and management of diabetes, are closely associated with depression, particularly as a concerning comorbidity [14]. Anxiety not only causes social and psychological consequences but also poses a significant threat to adherence to self-care regimes, thereby exacerbating diabetes-related complications, such as death anxiety. Additionally, death anxiety, another psychological factor, intricately affects metabolic processes by impacting diabetes management and blood sugar control. Managing chronic stress related to death anxiety presents considerable challenges for patients, as its physiological manifestations demand psychological attention [15]. Despite the documented correlations between psychological factors and diabetes outcomes, these complexities receive insufficient attention from healthcare providers. Furthermore, there are notable disparities in symptom recognition, levels of death anxiety, and acceptance of treatment methods, indicating the presence of racial and cultural variations in the manifestation and management of psychological issues within diabetic populations. While significant research has explored the link between AI and death anxiety in the context of diabetes, studies on the prevalence and co-occurrence of anxiety remain limited, particularly among specific populations.

As shown in Table 4, research concerning artificial intelligence and death anxiety can be broadly categorized into three thematic areas: anxiety detection, anxiety-related disorders and diseases, and specific populations affected by anxiety.

Anxiety Detection: A range of models and analytical techniques are employed to identify anxiety symptoms. For example, Kapoor et al. (16) utilized machine learning to assess human anxiety by analyzing data from Twitter posts. Many studies favor the use of physiological biomarkers, such as electrodermal activity (EDA), as input variables in machine learning models due to their high sensitivity and predictive accuracy (17). Facial expression recognition also remains a widely used and effective method for detecting anxiety (17).

Anxiety-Related Disorders and Diseases: Several studies focus on evaluating the effects of anxiety on specific clinical populations (17). In such cases, AI tools are often used to classify anxiety severity and suggest targeted therapeutic interventions. Some researchers also leverage AI to predict disease risk by analyzing psychological and physiological data (18).

Vulnerable Populations Affected by Anxiety: There is growing interest in understanding anxiety among specific groups, especially in relation to death anxiety. Researchers have explored the psychological states of individuals dealing with death-related stress (18) and other associated mental health challenges. For instance, Birnbaum et al. (19) applied deep learning techniques to examine how students' self-reported phobia concerns relate to their behaviors and mental well-being.

This classification framework highlights the breadth of AI applications in studying anxiety particularly within diabetic populations and emphasizes the importance of further research to address these complex psychological phenomena.

Table 4. Research Related to AI and Death Anxiety in Diabetic Populations

Date	Topic	Keywords	Coherence
2018–2019	Diabetes and death anxiety	Diabetes, anxiety, disorder, analysis, health, patient, depression, learning, symptoms, approach	0.54
	Anxiety prediction	Data, system, prediction, risk, disease, factor, model, research, diagnosis, state, discomfort, tension, restlessness	
	Anxiety's effect	Effect, health, application, pain, evaluation, testing, system, cancer, network, function	
	Anxious thoughts/anxiety disorder		
2020–2021	Diabetes and death anxiety	Diabetes, anxiety, disorder, analysis, health, patient, depression, symptoms	0.43
	Anxiety detection	Data, system, prediction, risk, disease, factor, model, research, diagnosis, state waiting for fear of generalized anxiety disorder (GAD)	
	Anxiety of students	Study, stress, networking, student, review, effect, artificial intelligence, brain	
2022.1–2023.3	Diabetes and death anxiety	Diabetes, anxiety, disorder, analysis, health, patient, depression, panic, discomfort, tension, restlessness	0.44
	Anxiety detection	Machine learning, health, disorder, study, analysis, patient, anxiety, depression, mood	
	Diabetes and death anxiety	Diabetes, anxiety, disorder, analysis, health, patient, depression, learning, symptoms	

According to the coherence score a metric used to evaluate the semantic correlation and consistency among variables in a dataset we can assess the psychological relevance of death anxiety across different thematic clusters. Analysis of the table reveals that topics linking diabetes and anxiety, particularly those related to phobic disorders, exhibit the highest coherence with fear of death. This suggests a stronger and more direct psychological association between death-related anxiety and phobia than with other examined topics.

In contrast, topics focused on sleep disorders show a weaker connection to death anxiety. This may be due to the nature of sleep disturbances, which often concern cognitive processing and information transfer between external stimuli and the brain, rather than direct associations with physical mortality. As such, they tend to attract comparatively less public concern and psychological emphasis regarding death. These findings imply that conditions involving physical vulnerability and mortality such as diabetes and phobia are more potent triggers of death anxiety than cognitive or behavioral conditions like sleep disorders.

4. DISCUSSION

Using artificial intelligence (AI), it is possible to support the diagnosis and management of death-related anxiety among individuals suffering from diabetes, phobias, and sleep disorders. By leveraging data analysis and AI technologies, researchers aim to enhance cognitive function, reduce anxiety symptoms, and promote positive psychological outcomes. An increasing number of studies have examined these three factors, with more attention given to combinations of two conditions than to all three simultaneously. This may reflect the difficulty of identifying study populations exhibiting all three conditions and the interdisciplinary expertise required for such research.

The growing prevalence of death anxiety has provided a compelling rationale for integrated investigations across these areas. Numerous studies have confirmed that death anxiety exacerbates symptoms associated with diabetes, phobias, and sleep disturbances. As a result, research addressing these topics in various combinations has proliferated, with cross-sectional findings revealing interconnected psychological and physiological mechanisms. Among the common research themes, anxiety and depression are frequently studied possibly because anxiety remains central to mental health discourse. Specifically, death anxiety is linked to elevated corticotropin levels, a stress hormone, suggesting that shared biological pathways may contribute to the comorbidity of these disorders.

Although societal fear surrounding death anxiety may gradually decline, the trend of scholarly research is expected to grow. Investigations carried out during times of heightened public anxiety have laid a strong foundation for future studies. Even after large-scale societal stressors diminish, their psychological consequences often persist, justifying continued exploration [20]. During the SARS outbreak, for instance, healthy individuals experienced psychological stress comparable to those with chronic conditions. One year later, increased rates of post-traumatic symptoms, anxiety, and depression were observed in the general population [21]. According to Jojoa et al., 30 months after the onset of death anxiety, the cumulative incidence of mental disorders had reached 58.9% [22], underscoring the long-term mental health implications.

As AI continues to evolve, its application to death anxiety research is projected to rise rapidly. Torous and Walker emphasize the potential of AI to deliver personalized insights through data-driven modeling [13], but they also warn of associated risks and complexities. Predictive models can forecast treatment outcomes, life expectancy, and rehabilitation progress, but their interpretation must be handled with caution. These models often draw on population-level datasets, which enhances training accuracy but introduces considerable uncertainty when applied to individuals [14]. This raises an important clinical question: how should patients and physicians interpret AI-generated prognoses based on aggregated healthcare data?

Linden and colleagues advocate for framing predictive outputs as probabilities rather than certainties [23]. Tools such as calibration testing can help assess the reliability of predictions, and transparent communication of such uncertainty is essential. However, every model is inherently limited by its data sources, underlying assumptions, and unknown factors that evolve over time. Algorithms trained on specific subpopulations may not generalize effectively to other geographic or clinical contexts [24]. These nuances can be difficult to interpret even for professionals and raise ethical concerns about how best to communicate model limitations [22].

Research using Latent Dirichlet Allocation (LDA) remains in an exploratory phase, with no standardized system yet in place. Nonetheless, the increasing integration of AI in mental health research has led to notable advances in diagnostic approaches. Many studies now use AI to identify depression and anxiety through diverse data analysis methods. While this trend is promising, large-scale, high-quality mental health data remains resource-intensive to collect [23]. As such, addressing data-related challenges will be a critical step in realizing the full potential of AI in mental health. Looking ahead, AI is poised to make substantial contributions to both the scientific understanding and clinical management of psychological conditions.

5. LIMITATIONS

This study has several limitations. First, the document retrieval process was confined to the Web of Science database, which may have resulted in the exclusion of relevant literature from other databases. Second, the search keywords employed were relatively basic and did not incorporate synonyms, potentially narrowing the scope of the retrieved results. Third, the analysis was limited to general comparisons of proportions and development trends, without conducting in-depth statistical examinations. Additionally, the LDA heat map was generated based solely on highly cited and high-impact research areas, without a thorough discussion of the broader literature. Furthermore, in the AI-LDA section, data cleaning and refinement were not exhaustively performed, leading to the inclusion of some studies that did not strictly align with the research focus. Overall, it is anticipated that future studies will develop a more robust and comprehensive AI-LDA model.

6. CONCLUSION

Topics related to artificial intelligence and death anxiety encompass several dimensions, which can broadly be categorized into three areas: identification of anxiety, anxiety-related disorders and diseases, and specific populations affected by anxiety. AI demonstrates considerable potential in detecting cognitive and physiological patterns linked to death anxiety through detailed analysis of textual and biological data. This capability facilitates improved diagnosis, prediction, and treatment of individuals experiencing this form of anxiety. The integration of the core components of Latent Dirichlet Allocation (LDA) has become increasingly common, especially in tackling the persistent challenges associated with death anxiety. Scientific interest in evaluating the performance of AI across diverse demographic groups has expanded, revealing a concerning intensification of anxiety symptoms among both mentally and physically ill patients. Within the AI-LDA domain, the progressive evolution of AI models has driven notable advancements in predicting and analyzing mental and cognitive disorders. These developments have opened new avenues for understanding and managing anxiety-related conditions, underscoring the transformative impact of AI in mental health research.

Artificial intelligence (AI) offers substantial potential in the field of mental health for the diagnosis and intervention of anxiety disorders, particularly those related to mortality. Recent research has demonstrated that data analysis from sensors and AI algorithms can provide early indicators of anxiety in patients. These markers include alterations in sleep patterns, physical activity, speech patterns, and physical movements. Studies have shown that AI can detect these changes with greater accuracy and speed, enabling healthcare professionals to deliver more effective treatments and interventions to alleviate patient anxiety. Furthermore, AI serves as a pivotal tool in enhancing diagnostic and therapeutic methods for anxiety disorders. Through the application of deep learning algorithms, anxiety-related behavioral and cognitive patterns can be identified in patients, thereby facilitating the development of more personalized and efficacious treatment plans. These tools not only enhance clinicians' understanding of patients' conditions but also improve counseling and support for patients and their families, which is crucial in addressing mortality anxiety.

Declaration

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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