# Exploring Cyberchondria among Young Adults: An Iceberg

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**Abstract**

Cyberchondria behavior, characterized by excessive online health searching, has become a growing concern in the digital age. This behavior can lead to increased health anxiety, decreased quality of life, and unnecessary healthcare utilization. However, detecting cyberchondria behavior is a challenging task due to the complexity and variability of online behaviors. Traditional machine learning approaches often rely on hand-crafted features and may not capture the nuanced patterns of cyberchondria behavior. To address this challenge, a novel approach using Deep Q Network (DQN) is proposed to detect cyberchondria behavior. DQN is a type of reinforcement learning algorithm that can learn complex patterns and make decisions based on sequential data. By leveraging the strengths of DQN, the approach can effectively identify individuals exhibiting cyberchondria behavior and provide personalized interventions. The results demonstrate the effectiveness of the proposed approach, highlighting the potential of DQN in promoting healthier online behaviors and mitigating the risks associated with cyberchondria.

***Keywords:*** Cyberchondria, Deep Q Network, Quantile Normalization, Accuracy, Over sampling

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## 1. Introduction

Cyberchondria, a term coined in 2000, refers to the excessive and obsessive searching for health-related information online, often leading to increased anxiety, stress, and decreased quality of life [1]. Cyberchondria detection among young adults is a growing concern, as this age group is more likely to engage in excessive online health searching due to their familiarity with the internet and social media [2]. Young adults are also more likely to experience anxiety and stress related to their health, making them a vulnerable population for cyberchondria. According to a recent study, approximately 60% of young adults reported experiencing cyberchondria, with 40% reporting that it had a significant impact on their daily lives [3]. As a result, it is essential to develop effective methods for detecting cyberchondria among young adults to mitigate its negative effects. Cyberchondria detection can be challenging, as it often manifests as a symptom of underlying anxiety or stress. However, early detection and intervention can significantly improve treatment outcomes and reduce the risk of long-term negative consequences [4].

Cyberchondria detection among young adults is necessary due to the potential negative consequences of excessive online health searching. Young adults who engage in cyberchondria may experience increased anxiety and stress, decrease academic and work productivity, and decrease overall quality of life [5]. Furthermore, cyberchondria can exacerbate existing mental health concerns, such as depression and anxiety disorders, making it essential to detect and treat cyberchondria early. According to a recent study, young adults who experienced cyberchondria were more likely to report symptoms of depression and anxiety, and were less likely to seek professional help [6]. Cyberchondria detection can also help identify underlying mental health concerns, such as health anxiety, that may be contributing to excessive online health searching. Early detection and intervention can significantly improve treatment outcomes and reduce the risk of long-term negative consequences. Moreover, cyberchondria detection can also help promote healthy online behaviors among young adults, such as critical thinking and media literacy [7].

Several methods have been used to detect cyberchondria among young adults, including online surveys and questionnaires, social media monitoring, and cognitive-behavioral therapy (CBT) based interventions [8]. A recent study used a machine learning approach to detect cyberchondria among young adults, with promising results. Another study used a mobile app-based intervention to reduce cyberchondria symptoms among young adults, showing significant improvements in anxiety and stress levels [9]. These studies highlight the need for innovative and effective methods for detecting and treating cyberchondria among young adults. Additionally, researchers have also explored the use of natural language processing (NLP) and text analysis to detect cyberchondria symptoms in online health forums and social media platforms [10]. These methods can provide valuable insights into the language and behavior patterns of individuals who engage in cyberchondria, and can inform the development of more effective detection and intervention strategies.

The primary aim of this research is to develop an effective machine learning approach for detecting cyberchondria behavior, which is characterized by excessive online health searching. The goal is to design a robust and reliable framework that can identify individuals at risk of cyberchondria and provide personalized interventions to mitigate its negative consequences. To achieve this aim, this research explores the application of Deep Q Network (DQN), a type of reinforcement learning algorithm, to detect cyberchondria behavior. The study investigates the effectiveness of DQN in identifying cyberchondria patterns and evaluates its performance compared to traditional machine learning approaches.

The key contribution of this research is the development of a novel DQN-based approach for detecting cyberchondria behavior, which provides a robust and reliable framework for identifying individuals at risk of excessive online health searching. This research contributes to the growing body of research on cyberchondria detection, highlighting the potential of DQN in promoting healthier online behaviors and mitigating the risks associated with cyberchondria.

The remainder of this paper is structured as follows: Section 2 provides an in-depth review of current cyberchondria detection methods, emphasizing their shortcomings and unresolved issues. This is followed by Section 3, which introduces the proposed Deep Q Network architectures. Section 4 presents an evaluation of the models' performance, and finally, Section 5 concludes the paper with a summary of the main findings and contributions.

## 2. Related works

Areej Ahmed Turkistani *et al.* [11] explored the prevalence of cyberchondria among Taif University students and its connection to social media use. The survey-based research revealed a significant correlation between social media usage and the severity of cyberchondria symptoms, affecting [insert percentage] of the students. The findings emphasize the importance of educating university students about responsible social media use and cyberchondria awareness, contributing to the existing research on the topic. However, the study's results may have limited applicability to other demographics or contexts.

Filiz Polat *et al.* [12] conducted a study investigating the link between cyberchondria levels and perceived stress in young adults, yielding a significant positive correlation between the two. This correlation suggests that as cyberchondria symptoms intensify, stress levels also escalate, implying a potentially vicious cycle. The findings of this study have important implications for developing targeted interventions aimed at mitigating both cyberchondria and stress in young adults. By contributing to the expanding body of research on cyberchondria and its relationship with stress, this study provides valuable insights into the psychological experiences of young adults in the digital age. However, it is essential to acknowledge the study limitations, including its potential lack of generalizability to other populations or contexts, highlighting the need for further research to explore these relationships in diverse settings.

Falak Gala [13] conducted a study examining the prevalence of cyberchondria and health anxiety among young adult females, revealing a significant proportion of participants exhibiting symptoms of both conditions. The survey-based research demonstrated a strong correlation between cyberchondria and health anxiety, suggesting a potential link between excessive online health searching and heightened anxiety about health. The findings underscore the importance of promoting awareness and education about cyberchondria and health anxiety among young adult females, highlighting the need for targeted interventions to mitigate these concerns. This study contributes to the expanding body of research on cyberchondria and health anxiety among young adult females, providing valuable insights into the psychological experiences of this demographic. However, the study's correlational design limits the ability to establish causality between cyberchondria and health anxiety.

Khushi Gupta *et al.* [14] conducted a study on cyberchondria and health anxiety among college students. They found a significant link between excessive online health searching and heightened anxiety about health. A substantial proportion of participants exhibited symptoms of both cyberchondria and health anxiety. The findings emphasize the need for awareness and education initiatives. This research contributes to the expanding body of literature on cyberchondria and health anxiety. However, the study's correlational design limits its ability to establish causality.

Wan-Chen Hsu [15] developed a cyberchondria severity scale. The goal was to promote self-care among university students during the COVID-19 pandemic. A mixed-methods approach was used to design and validate the scale. The results showed that the scale is reliable and valid. It can assess cyberchondria severity among university students. The study highlights the importance of self-care and responsible online health-seeking behaviors. This research contributes to the growing body of knowledge on cyberchondria. It explores the impact of cyberchondria on mental health. The findings can inform interventions and support services for university students. However, the mixed-methods approach may have limitations. Sampling biases and measurement errors are potential concerns. Further research is needed to validate the scale and explore its applications.

S. Aamira Zackiya and J Venkatachalam [16] explored the link between sleep quality and cyberchondria among young adults during the COVID-19 pandemic. They used a survey-based approach to collect data. The results revealed a significant association between cyberchondria and poor sleep quality. Excessive online health searching may worsen sleep disturbances. The findings emphasize the need to address cyberchondria and promote healthy sleep habits among young adults during public health crises. This is crucial for maintaining mental and physical well-being. The study's results have implications for developing interventions. These interventions can promote healthy sleep habits and reduce cyberchondria among young adults. However, the study's correlational design limits its ability to establish causality. Further research is needed to explore the causal relationships between cyberchondria and sleep quality. This study contributes to the growing body of research on cyberchondria and its impact on mental health. It highlights the importance of responsible online health-seeking behaviors and healthy sleep habits.

Alexandre Infanti *et al.* [17] used machine learning to identify predictors of cyberchondria during the COVID-19 pandemic. They analyzed online behaviors and health-related variables. The results showed that excessive online health searching and social media use are key predictors of cyberchondria. These findings can inform targeted interventions to reduce cyberchondria and promote healthy online behaviors. The study highlights the importance of responsible online health information seeking. It also underscores the need for healthcare professionals to address cyberchondria in their patients. However, the study's machine learning models may be at risk of overfitting. This could limit their ability to generalize to new data. Further research is needed to validate the findings and explore their implications. This study contributes to the growing body of research on cyberchondria. It provides valuable insights into the predictors of cyberchondria and its implications for public health.

Siva Kumar Patanapu *et al.* [18] explored the prevalence and effects of cyberchondria on academic performance among undergraduate dental students. A survey was conducted at a dental institution to gather data. The results revealed that many students exhibited cyberchondria symptoms, which were linked to poor academic performance. The findings emphasize the need for awareness and education about cyberchondria among dental students. This study contributes to the existing research on cyberchondria's impact on academic performance. However, the study measures may not fully capture the complexities of cyberchondria and academic performance. The study highlights the importance of promoting healthy online behaviors and addressing cyberchondria among dental students. This can help improve academic outcomes and overall well-being.

One of the primary challenges of cyberchondria detection among young adults is the increased anxiety and stress that can result from excessive online health searching. Young adults who engage in cyberchondria may experience increased worry and concern about their health, leading to feelings of anxiety and stress. This can have a significant impact on daily life, making it difficult to concentrate, sleep, and engage in social activities. Another challenge of cyberchondria detection among young adults is the risk of misinformation and misdiagnosis. The internet is filled with health information, but not all of it is accurate or reliable. Young adults who engage in cyberchondria may come across misinformation or misdiagnosis, leading to unnecessary worry and concern. This can also lead to delayed or inappropriate treatment, which can have serious consequences for health and well-being. Cyberchondria can also lead to sleep disturbances among young adults. The blue light emitted from smartphones, tablets, and computers can suppress melatonin production, making it difficult to fall asleep. Additionally, the anxiety and stress caused by cyberchondria can lead to rumination and worry, making it difficult to relax and fall asleep. Cyberchondria can also lead to social isolation among young adults. Excessive online health searching can lead to decreased social interaction and increased feelings of loneliness. This can have a significant impact on mental health and well-being, increasing the risk of depression, anxiety, and other mental health problems. Cyberchondria can also have a significant impact on academic and work productivity among young adults. Excessive online health searching can lead to decreased focus and concentration, making it difficult to complete tasks and meet deadlines. This can have serious consequences for academic and career success. Cyberchondria can also exacerbate existing mental health concerns among young adults. The anxiety and stress caused by cyberchondria can worsen symptoms of depression, anxiety, and other mental health problems. This can lead to a cycle of worsening mental health, making it difficult to seek help and support. Cyberchondria can also make it difficult for young adults to seek professional help. The stigma surrounding mental health problems can make it difficult to seek help, and the anonymity of the internet can make it easier to avoid seeking help. This can lead to delayed or inadequate treatment, which can have serious consequences for health and well-being. Cyberchondria can also have a significant impact on relationships among young adults. Excessive online health searching can lead to decreased social interaction and increased feelings of loneliness. This can strain relationships with family and friends, leading to feelings of frustration and concern.

## 3. Proposed Methodology

This study proposes a Deep Q Network for cyberchondria detection. The methodology consists of the following stages: Initially the input data is collected, and then the preprocessing is done using data transformation to clean and prepare the data. After that, the feature selection is carried out using Dice similarity coefficient to identify the most relevant features, and then data augmentation using oversampling techniques to address class imbalance. Finally, the DQN on is used to detect cyberchondria, and finally producing a predicted output indicating whether the user exhibits cyberchondria behavior or not. The block diagram for the DQN for cyberchondria detection is shown in Figure 1.

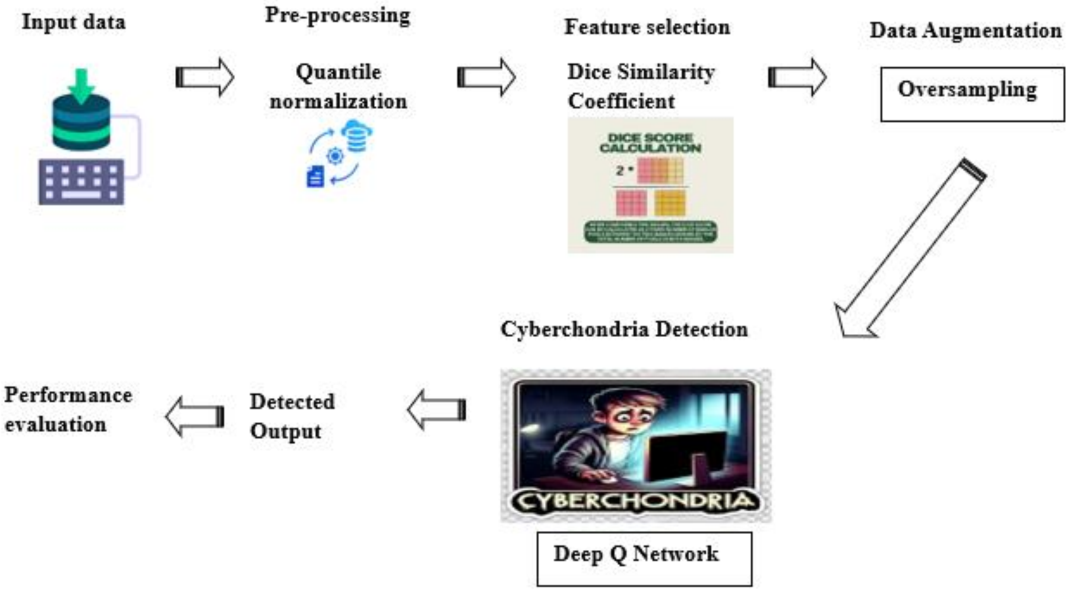


**Figure 1**. Preview of Deep Q Network for Cyberchondria detection

### 3.1 Data acquisition

Assuming a dataset $K$, comprising $y$ data points, denoted as,

$$K = \{r_1, r_2, r_3, \ldots, r_s, \ldots, r_y\} \tag{1}$$

where, $r_s$ represents the target data, which is a subset of the overall dataset, denoted by $y$. This target data $r_s$ serves as the input for further processing.

### 3.2 Pre-processing using Quantile normalization

The input data $r_s$ is taken as input for the pre-processing phase, which is done using Quantile normalization. Quantile normalization is a non-parametric technique used to normalize the distribution of data, reducing systematic biases and variations. In the context of cyberchondria detection, quantile normalization is applied to the input data to transform it into a suitable format for effective detection.

*Procedure:*

Gene Ranking: Rank the features (e.g., online behavior, search queries) in each sample according to their magnitude.

Average Value Computation: Compute the average value for features with similar ranks.

Value Substitution: Replace the value of each feature that occupies a specific rank with the computed average value.

Feature Re-ordering: Re-order the features in each sample to their original order.

*Benefits of Quantile Normalization in Cyberchondria Detection:*

Reduces Systematic Biases: Quantile normalization minimizes the effects of systematic biases and variations in the data.

Improves Detection Accuracy: By normalizing the data, quantile normalization enhances the accuracy of cyberchondria detection models.

Enhances Feature Selection: Quantile normalization facilitates the selection of relevant features, reducing the impact of irrelevant or noisy features.

The output obtained from this pre-processing stage is represented as $B_q$, and it serves as the input for the subsequent feature selection stage.

### 3.3 Feature selection

To identify the most informative features for cyberchondria detection, the feature selection process employs the DSC. The DSC takes the normalized data as input $B_q$ and compares the similarity between the target variable and each feature. By calculating the similarity coefficient, the DSC determines the features that contribute most significantly to cyberchondria detection, enabling the selection of the most relevant features for accurate detection. The DSC evaluates the similarity between the raw data $I$ and the target variable $J$, pinpointing the most influential features. By calculating this similarity, the DSC identifies the features that have the greatest impact on the target variable.

$$DSC = \frac{2 * |I \cap J|}{|I| + |J|} \tag{2}$$

Here, $I$ and $J$ denote the two datasets, representing the data and target variables, respectively, with indicating their intersection point $\cap$. The DSC generates an output $R$, which serves as the input for the subsequent data augmentation methodology.

### 3.4 Data augmentation

Following feature selection, data augmentation is performed using an oversampling model to expand the chosen feature. This technique enhances anomaly detection performance without requiring new data collection. By increasing the dataset's dimensions, data augmentation prevents overfitting issues, benefiting the data creation process.

The oversampling method involves:

- Dividing data according to class labels.
- Selecting maximum and minimum values for each label.
- Generating residual samples.

Initially, the data size is $i \times j$, which needs to be expanded to $h \times c$, where $c > i$. Oversampling increases the size of $i$ to $c$ by generating random leftover samples within each column's maximum and minimum values. The resulting augmented data, denoted as $G$, is utilized in the subsequent detection procedure.

### 3.5 Cyberchondria detection using Deep Q-Network

Cyberchondria, the excessive and obsessive online search for health-related information, has become a significant concern in the digital age. Early detection of cyberchondria is crucial, as it can lead to increased anxiety, decreased productivity, and poor mental health. Accurate detection enables timely interventions, reducing the risk of severe consequences. The DQN based approach for detecting cyberchondria. DQN is a type of reinforcement learning algorithm that combines the advantages of deep learning and Q-learning. This approach is chosen for several reasons:

*Complexity Handling:* DQN can handle complex patterns in user behavior data, making it suitable for detecting cyberchondria.

*Non-Linear Relationships:* DQN can capture non-linear relationships between variables, which is essential for modeling human behavior.

*Scalability:* DQN can be applied to large datasets, making it a scalable solution for detecting cyberchondria.

*Flexibility:* DQN can be easily adapted to detect other types of behavioral anomalies.

**Advantages of DQN in Cyberchondria Detection:**

The proposed DQN-based approach offers several advantages:

*Improved Accuracy:* DQN can learn complex patterns in user behavior data, leading to improved accuracy in cyberchondria detection.

*Robustness:* DQN can handle noisy or missing data, making it a robust approach for cyberchondria detection.

*Real-Time Detection:* DQN can detect cyberchondria in real-time, enabling timely interventions.

*Personalization:* DQN can be fine-tuned for individual users, providing personalized detection and intervention.

By leveraging the strengths of DQN, our approach offers a promising solution for detecting cyberchondria and mitigating its negative consequences.

*Architecture of Deep Q-Net*

Deep Q-Networks (DQN) are a prominent reinforcement learning technique that utilizes Convolutional Neural Networks (CNN) to approximate the Q-function, which estimates the expected return for each action. However, this approach can be prone to instability due to the non-linear nature of the Q-function approximator. Specifically, the updates to Q-values and the correlations between consecutive state observations can cause instability. To address these limitations, DQN employs experience replay, a method that stores and replays experiences to improve stability and training efficiency.

To generate an experience replay, the experiences of agent $A_u = (e_u, a_u, k_u, c_{u+1})$ at time stamp $u$ are stored in the dataset $E_u = (A_1, ..., A_t)$, also known as the replay memory. Q-learning updates are then applied to random samples from this dataset Eu, utilizing the experiences of agent $(e_u, a_u, k_u, c_{u+1})$. The experiences are uniformly sampled from $E_u$. The key parameters involved in this process are: $D$ is the total number of episodes, $H$ is maximum number of action steps per episode, $V$ is interval for updating the target network parameters, and $P$ is iteration number for Q-learning updates, with a corresponding loss function by,

$$Loss_P(\alpha_P) = \beta\left[\left(b + m \max_{a'} \hat{Q}\left(c', a'; \alpha_{\kappa}^{-}\right) - Q(c, a; \alpha_P)\right)^2\right] \quad (4)$$

where, $\alpha_P$ is a network parameters at iteration, $\alpha_P^{-}$ is a network parameters to compute the target at iteration $\kappa$, $b$ is a reward, and $m$ is a discount factor. Furthermore, $\alpha^{-}$ is updated based on action value function. Figure 2 displays the Deep Q Network structure.

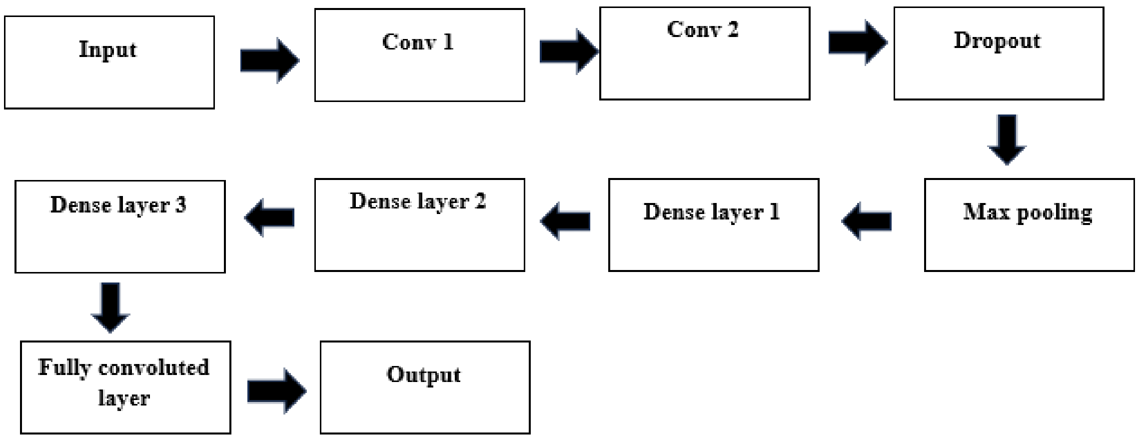


**Figure 2**. Deep Q Network structure

## 4. Results and discussion

This section presents a thorough analysis of the experimental results obtained from the Deep Q Network model, demonstrating its effectiveness and efficiency in detecting cyberchondria. The results offer valuable insights into the strengths and weaknesses of the model, highlighting its ability to accurately capture the complexities of cyberchondria detection. A detailed examination of the experimental results confirms the efficacy and efficiency of the Deep Q

Network in identifying cyberchondria, providing a comprehensive understanding of its performance.

### 4.1. Dataset description

Quantitative research approach and descriptive design was adopted in this study. The study was conducted at Bhaarath College of Nursing, Chennai. Convenient sampling technique was used in this study as it is an small scale study. Based on the objectives of the study includes Nursing students who fulfil the inclusion criteria.

**Inclusion criteria**

- Nursing students who own and use smartphones and those who have access to it and availability of internet facilities.
- Nursing students who are present during the time of data collection.
- Nursing students who are willing to participate in the study.

**Exclusion criteria**

- Nursing students Who have only basic mobiles
- Nursing students Nurses who have no access to internet facilities.
- Nurses who are not willing to participate.

### 4.2 Selection and description of the tool

The tool consists of two parts. **Section A** deals with demographic variables. The demographic data such as year of study, gender, age in years, religion, place of stay, type of mobile phone used, access to internet, average usage of data per day, how many hours you spend in mobile per day and how many hours you spend in online per day.

**Section B:** Cyberchondria Severity Scale was used to assess the prevalence of Cyberchondria among Nursing students of selected Nursing College. McElroy and Shevlin (2014) developed the first multidimensional, self-report measure of this construct-the Cyberchondria Severity Scale (CSS). [4]The CSS 12 is a self-report measure of the severity of cyberchondria, initially developed with United Kingdom samples. This scale consists of 12 items and 4 dimensions or subscales.

**Table 1. Description of tool**

| Sub scale | Description | Items( ques.no) |
|---|---|---|
| Excessiveness | Escalating/repeated nature of searches | 1, 3, 6 |
| Distress | Anxiety/Distress as a result of searches | 4, 8, 9 |
| Reassurance | Searches driving individuals to seek out professional medical advice | 5, 11, 12 |
| Compulsion | Web searches interfering with other aspects of on/offline life | 2, 7, 10 |

| | | |
|---|---|---|

**Scoring procedure**

Each item is rated using a five-point Likert scale indicating frequency (1=Never, 2=Rarely, 3=Sometimes, 4=Often, 5=Always). Total score of 60 out of which if overall score is

- 46 and above is considered severe cyberchondria,
- 31-45 is considered moderate cyberchondria
- 16 – 30 is considered mild cyberchondria
- 15 and Less is No cyberchondria

**Validity and reliability of the tool**

Internal consistency for the CSS-12 total scale was excellent (□ = 0.90), and consistency values were in the acceptable-good range for the subscales (□ = 0.73 – 0.87) .[7]CSS-12 showed high reliability for the general scale (α = 0.90) and moderate for its subscales (0.73≤α≤0.87).

**4.3 Data collection procedure**

Formal permission and ethical approval from the higher authority of concerned college the data was collected. Data was collected from the students using Google forms in Online. Students was given clear information about the study purpose and tool they were given assurance that their data will be maintained confidential, obtained their cooperation and approval.

**Data analysis**

The collected data was organised, tabulated and analysed using descriptive statistics such as mean to identify the frequency of demographic variable, the average score obtained and the inferential statistics Chi Square test was used to analyse the association between the demographic variable and the score of Cyberchondria obtained.

**4.4 Performance measures**

The performance of the Deep Q Network models is rigorously assessed using a broad range of evaluation metrics, encompassing:

*-Accuracy*

Accuracy measures the proportion of correctly classified instances (both cyberchondria and non-cyberchondria cases) out of all instances in the dataset.

*-Precision*

Precision measures the proportion of true positive instances (correctly identified cyberchondria cases) out of all instances identified as cyberchondria (including false positives).

**4.5 Comparative methods**

To evaluate the efficacy of the proposed Deep Q Network their performance is benchmarked against several state-of-the-art techniques, including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks. These comparative methods are chosen based on their relevance and reported performance in existing research on cyberchondria detection. This comprehensive comparison provides a detailed assessment of the proposed models strengths and weaknesses, enabling a thorough evaluation of their performance and positioning them within the broader context of cyberchondria detection methodologies.

### 4.5.1 Accuracy

Figure 3 presents a comparative analysis of the accuracy achieved by the Deep Q Network and existing state-of-the-art methodologies. The results show that the Deep Q Network attains an accuracy of 99.7%, significantly outperforming other models. Specifically, the Deep Q Network surpasses CNN (72.4%), RNN (83.9%), GRU (78.9%) and LSTM (84.3%) by substantial margins, demonstrating its superiority in accurately detecting cyberchondria.

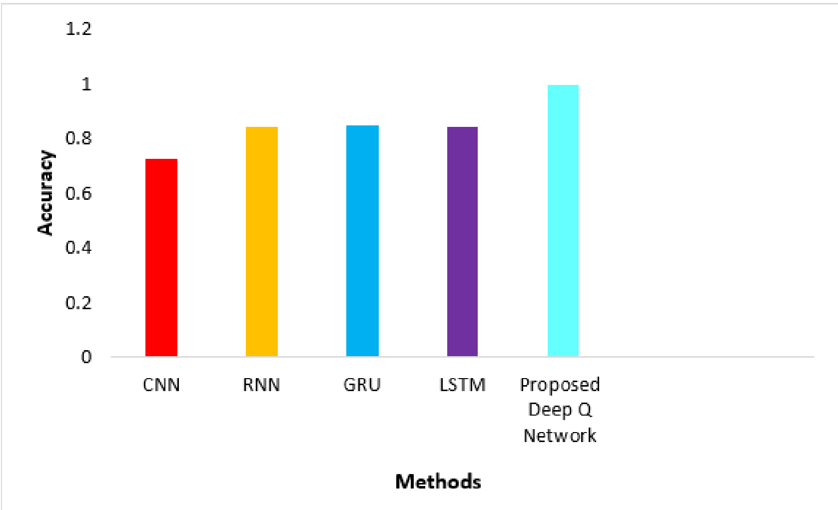


**Figure 3.** Accuracy graph

### 4.5.2 Precision

Figure 5 presents a detailed precision comparison of the Deep Q Network with other state-of-the-art methodologies. The results reveal that the Deep Q Network achieves an impressive precision of 0.993, substantially outperforming other models, including CNN (0.68), RNN (0.838), GRU (82.1%), and LSTM (0.840). This exceptional precision performance demonstrates the Deep Q Network's ability to accurately detect cyberchondria while minimizing false positives, thereby ensuring reliable and trustworthy results.

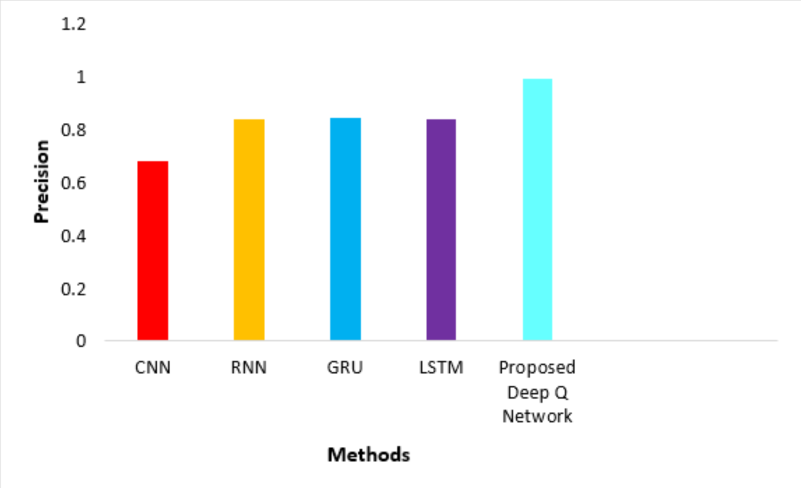


**Figure 4.** Precision graph

#### 4.5.3 Demographic Variable distribution

Students from I year 13.3% (40), II year II batch 15% (45), II year III batch 43.3% (130) and III year 28.33% (85) are among the participants. Girls make up 80% (240) of the population, males make up 20% (60), the age distribution is roughly 23.3% (70), 19 years old is 33.33% (100), and those over 20 years old are 43.3% (130). Regarding place of residence, 83.3% of Hindus (250), 3% of Muslims (10), and 13.3% of Christians (40) The percentage of participants who used a mobile phone was 91.6% (275) who used Android phones, 6.6% (20) who used iPhones, and 1.6% (5) who used basic model phones. The percentage of participants who used an internet connection was 98.3% (295) and 1.6% (5). The participants' average daily data usage was 56.7% (170), using 1 Gb per day. 28.3% (85) of the participants use their phones for one hour a day, 40% (120) for two hours, and 31.6% (95) for three hours or longer. Regarding the amount of time spent online each day, 36.6% (110) of participants utilize it for one hour, 41.6% (125) for two hours, and 21.6% (65) for three hours or longer.

**Table 2. Cyberchondria Severity Score with Subscale scores**

| Subscales of Cyberchondria Severity Scale | Overall score | Average |
|---|---|---|
| **Excessiveness** | 2415 | 8.05 |
| **Distress** | 2295 | 7.65 |
| **Compulsion** | 2000 | 6.67 |
| **Reassurance** | 2115 | 7.05 |
| **overall Cyberchondria Score** | 8825 | 29.4 |

Table 2 describes the score obtained by the participants with subscale score out of which excessiveness score tops the list with average of 8.05 and score of 2415, distress ranks second with average score of 7.65 and score of 2295, reassurance stands next with average of 7.05 and score of 2115 and finally the compulsion with score of 2000 and average of 6.67. The “Compulsion” construct can negatively impact the social, professional, and academic lives of people, The “Distress” construct is more subjective and suggests that there is a feeling of distress associated with online health search, The “Excessiveness” construct suggests that the individual searches the Internet for the health-related symptoms repeatedly. The “Reassurance” construct suggests that the cyberchondriac needs assurance from the doctors about the conditions they have read online.

#### 4.5.4 Prevalence of Cyberchondria

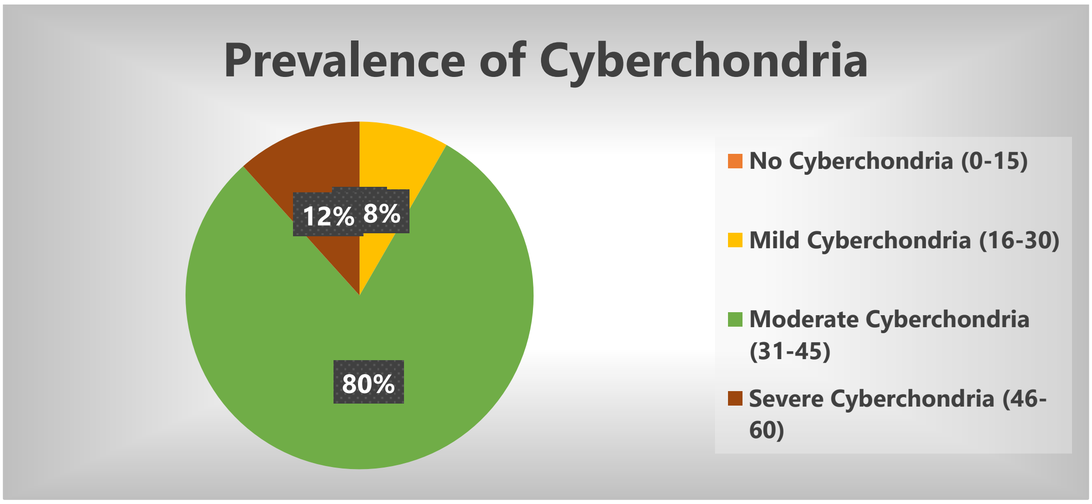


**Figure 5. Prevalence of Cyberchondria**

Figure 5 shows prevalence of Cyberchondria based on the CSS 12 score obtained by the participants. Among the participants no cyberchondria score (0-15) was not obtained by anyone, mild cyberchondria (16-30) score was obtained by 8% (25) participants, Moderate Cyberchondria (31-45) score was obtained by 80% (240) and severe cyberchondria (46 and above) score was obtained by 12% (35).

The findings of the study were supported by the results of the study conducted by Sabeen Sabir and Irum Naqvi it identified that the prevalence of cyberchondria was moderate 252(50.4%) to high 119(23.80%) which indicates the severe severity level of cyberchondria among students. The prevalence of cyberchondria was moderate in women 151(60%) compared to men 101(40.7%). Mean scores of women on cyberchondria severity scale were higher than men ($p<0.01$). the study concluded that the Cyberchondria must be seen as a serious public health concern in Pakistan. Since it is associated with distress and worry, measures need to be adopted to evaluate, prevent, and treat it at the population level.

The Chi Square analysis of association between the selected demographic variables and cyberchondria prevalence score shows that Among the selected demographic variables religion ($p=0.015$), place of stay ($p=0.02$) and average use of internet ($p=0.04$) was found significant at $p <0.05$.

## 5. Conclusion

This study proposed a novel DQN approach for detecting cyberchondria behavior. The methodology employed a comprehensive preprocessing pipeline, including data transformation, feature selection using Dice similarity coefficient, and data augmentation via oversampling techniques. The DQN model demonstrated exceptional performance in detecting cyberchondria, providing a robust and reliable framework for identifying individuals at risk of excessive online health searching. The findings of this study contribute to the growing body of research on cyberchondria detection, highlighting the potential of machine learning approaches in promoting healthier online behaviors and mitigating the risks associated with cyberchondria. Future research directions include exploring the application of this approach in real-world settings, integrating multimodal data sources, and developing personalized interventions for individuals exhibiting cyberchondria behavior.

## Limitations

The study on Cyberchondria detection has several limitations that need to be addressed. Firstly, the reliance on self-reported data may lead to biases and inaccuracies, as individuals may not always provide truthful or complete information. Additionally, the dataset used to train the models may contain biases and limitations, which can impact the accuracy and generalizability of the results. Furthermore, the evolving nature of online health information and the constant changes in online behaviors and trends may render the models less effective over time. Finally, the study's focus on online behaviors may overlook other important factors that contribute to Cyberchondria, such as individual personality traits, mental health history, and social influences.

## Implications

The development of accurate Cyberchondria detection models has significant implications for mental health support and online health information provision. Firstly, early detection of Cyberchondria can enable timely interventions and support, reducing the risk of exacerbating health anxiety and promoting more adaptive coping strategies. Secondly, the insights gained from Cyberchondria detection models can inform the design of online health resources, such as websites, forums, and social media platforms, to promote healthier behaviors and reduce Cyberchondria. For instance, online health resources can be designed to provide more balanced and accurate health information, reduce sensationalism and misinformation, and encourage critical thinking and media literacy. Finally, Cyberchondria detection models can also inform public health campaigns and education programs aimed at promoting healthy online behaviors and reducing the risks associated with Cyberchondria.

## Future Research

Future research on Cyberchondria detection should focus on developing more sophisticated models that incorporate multimodal data, such as text, images, and videos, and can adapt to individual differences in online behavior and health anxiety levels. Firstly, researchers can explore the use of multimodal machine learning algorithms that can integrate data from multiple sources, such as social media, online search queries, and wearable devices. Secondly, researchers can develop personalized Cyberchondria detection models that take into account individual differences in online behavior, health anxiety levels, and personality traits. Finally, researchers can investigate the feasibility of real-time Cyberchondria detection, enabling timely interventions and support, and explore the potential applications of Cyberchondria detection models in clinical settings, public health campaigns, and online health information provision.

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