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A Comprehensive Multidimensional Analysis of Mental Health Challenges in the Digital Age

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ABSTRACT

The digital era has introduced mental health challenges, especially for youth. Despite increasing awareness, comprehensive analyses of these challenges remain limited. This study collects and examines the prevalence of 15 key mental health challenges related to digital engagement, based on a sample of 555 participants. The prevalence of these challenges varied, with pressures related to parenting, hoarding, and inappropriate content being the most common, affecting 60.13%, 52.76%, and 45.39% of the participants, respectively. The research also highlights gender and age differences, noting that males report higher levels of issues like FOMO and Nomophobia compared to females. Adults (18+) face more severe challenges, such as memory decline, while younger individuals report fewer problems. Correlation analysis revealed significant relationships between several mental health challenges, such as Nomophobia and TAD (r = 0.68) and FOMO and TAD (r = 0.50), indicating that individuals experiencing one challenge are likely to face others. A decision tree analysis was used to predict mental health challenges by examining the relationships between different mental health conditions, uncovering specific patterns and rules associated with the occurrence of these challenges. Additionally, cluster analysis in this study identified distinct population segments, with 21% of individuals falling into a cluster that experiences severe mental health challenges. The findings suggest that a significant portion of the population is at risk for severe mental health issues, highlighting the need for targeted interventions.

Keywords— Digital Age, Mental Health Challenges, Statistical Analysis, Machine Learning.

1. Introduction

The advent of digital technology has transformed various aspects of modern life, including communication, education, and entertainment. While these advancements have facilitated unprecedented access to information and global connectivity, they have also introduced new challenges, particularly in the realm of mental health. The increasing reliance on digital devices and social media platforms has been linked to various mental health issues, especially among young individuals, who are particularly vulnerable to the pressures and stressors of the digital age [1].

While the benefits of technology are undeniable—enhancing learning opportunities, fostering social interactions across geographical boundaries, and providing a vast array of entertainment options [2]—the negative implications for mental health cannot be ignored. Recent studies suggest that constant digital engagement contributes to heightened levels of stress, anxiety, and social comparison, exacerbating existing mental health conditions [3]. The pressure to maintain an idealized online persona, combined with excessive screen time and exposure to potentially harmful content, is increasingly associated with mental health disorders such as depression and anxiety [4].

Moreover, the emergence of specific psychological phenomena, such as Nomophobia (the fear of being without a mobile phone) and FOMO (fear of missing out), highlights the unique challenges posed by constant digital connectivity [5]. These concerns are particularly acute among young people, who are still developing the coping mechanisms needed to navigate the complexities of both digital and real-world interactions [6]. The correlation between increased digital consumption and rising

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rates of mental health issues, such as depression, anxiety, and even suicide among adolescents, is particularly alarming [7].

The financial and emotional toll of mental health disorders underscores the importance of addressing these challenges at both individual and societal levels. The cost of treatment, combined with often underfunded mental health services, highlights the critical need for prevention and early intervention [8]. Digital literacy and responsible technology use have become essential skills, alongside traditional life skills, for maintaining mental well-being in an increasingly digital world.

Despite the growing recognition of these issues, there remains a significant gap in the literature regarding a comprehensive, multidimensional analysis of mental health challenges linked to digital engagement. Most existing studies focus on individual challenges in isolation without exploring the complex interrelationships between them or their combined impact on different population segments.

Additionally, the interrelationships between different mental health challenges remained largely unexplored, limiting our understanding of how various digital-age stressors might work in concert to affect mental well-being. Another significant shortcoming in the existing literature was the lack of a comprehensive understanding of how these challenges manifest across different demographic groups.

Our study addresses the above gaps by conducting an in-depth analysis of key mental health challenges. In our research, a holistic methodology is employed through which 15 different mental health challenges are examined simultaneously, enabling a comprehensive understanding of the digital age's impact on mental well-being. Relationships between various challenges are uncovered through the application of advanced statistical methods, including correlation analysis, decision trees, and cluster analysis. These methodological approaches provide unprecedented insights into how different mental health challenges interact and influence one another in the digital context.

Through detailed demographic analysis, a deeper understanding of how these challenges affect different population segments has been achieved. This granular examination reveals important variations in how different age groups and genders experience and cope with digital-age mental health challenges. Furthermore, quantitative metrics for the prevalence of various challenges have been established, providing a robust baseline for future research and interventions.

By analyzing the correlations, we unveil the interconnections and dependencies among various mental health issues, providing valuable insights into how these challenges interact and influence one another within the digital context.

The use of decision tree analysis in this context is particularly valuable as it allows for the identification of specific rules and significant predictors of mental health challenges. This method not only enhances interpretability but also reveals the complex interactions among various mental health issues, facilitating a nuanced understanding of how multiple factors contribute to mental health outcomes.

A segmentation model is developed to identify high-risk groups, enabling more targeted and effective interventions. This segmentation approach represents a significant advancement in understanding the distribution and severity of mental health challenges across different population groups.

Through this comprehensive approach, not only have the existing gaps in literature been addressed, but a foundation has been laid for future research in this critical area.

The research addresses the following questions:

- **RQ1**: What are the primary mental health challenges in the digital age?
- **RQ2**: How do mental health challenges vary across demographics such as age and gender?
- **RQ3**: What is the distribution of mental health challenges?
- **RQ4**: What are the relationships between different mental health challenges in the digital age?
- **RQ5**: What are the main segments of people experiencing mental health challenges, and how do these groups differ?

This paper is organized as follows: Section 2 provides a review of related work on analyzing mental health challenges associated with the use of digital technology. In Section 3, we detail a systematic approach for collecting and analyzing data related to mental health issues in the digital age. Section 4 presents the findings from the analysis, including mental health challenges, descriptive statistics on the prevalence of various issues, insights gained from proportion and correlation analyses, as well as classification and clustering methods. Finally, Section 5 summarizes the key insights from the research, discusses the study's limitations, and offers recommendations for future research.

2. Related Work

The impact of digital technology on mental health has garnered significant research attention, with studies examining various psychological challenges across different contexts. This section reviews relevant literature in five key areas: first, examining how age and gender influence digital mental health challenges; second, investigating the prevalence rates of various digital-age mental health issues across different populations; third, exploring the relationships and correlations between different mental health challenges in the digital age; fourth, analyzing prediction methods for identifying mental health challenges using machine learning approaches; and fifth, examining how clustering techniques can identify distinct patterns and categories of mental health challenges.

2.1. Age Groups and Genders

Pritam & Sarbil [24] conducted a comprehensive study examining smartphone addiction patterns across different age groups and genders. Their methodology involved surveying 1,200 participants from diverse age groups. The study revealed distinct patterns in smartphone usage and addiction across generations, with notable differences between adolescents and adults. Their findings indicated that while younger users showed a higher frequency of smartphone use, adults demonstrated more severe addiction symptoms. Regarding gender differences, male participants exhibited significantly higher levels of technology-related anxiety and dependency behaviors.

A study was conducted by Noorbehbahani et al. to assess the contributing factors related to decision-making loss. [25]. The study relied on data from 550 people in Isfahan, Iran. The results showed that decision-making loss was slightly more prevalent in females than males, but this difference was not statistically significant. However, individuals aged between 26-35 showed a substantial correlation with decision-making loss, while other age groups did not.

2.2. Prevalence of Mental Challenges

Alhaj et al [26] conducted research In which 232 female and 103 male undergraduate students from UAE took part. The research aimed to figure out the link between Nomophobia and FOMO with Depression, Anxiety, and stress among university students. The results revealed that 28.6% of respondents exhibited severe, 47.7% moderate, and 23.7% mild Nomophobia symptoms. 52.5% of participants reported moderate to extreme fear that others have more rewarding experiences than them, with the median FOMO score being (25.62).

Tomczyk and Lizde [27] conducted a study to measure the prevalence of Nomophobia and Phubbing in the family among adolescents in Bosnia and Herzegovina. They found that About 1/3 of the respondents declare having symptoms of Nomophobia and 9.87% of adolescents have a high saturation of Phubbing.

2.3. Correlations between Mental Challenges

Another research by Manzoor & Akhtar [28] examined multiple aspects of digital behavior patterns. They identified significant relationships between smartphone usage intensity and various psychological outcomes. The study found a strong relationship between smartphone addiction, FOMO, and mental health issues among young adults. The results support the hypothesis that smartphones significantly impact young adults' mental health.

A comprehensive review by Sulaiman et al. [19] has measured the impact of social media on mental health, encompassing both positive and negative dimensions. The results found that while social media can enhance social support and connectivity, it also poses significant risks, particularly in the form of cyberbullying and social comparison.

Another study by Franchina et al. [29] studied the relationships between FOMO, social media use, problematic social media use (PSMU), and Phubbing among 2,663 Flemish teenagers. They found that FOMO positively predicted the number of social media platforms used, the frequency of using major platforms like Facebook, Snapchat, Instagram, and YouTube, as well as PSMU and Phubbing behavior, both directly and indirectly through PSMU.

Wu et al. [30] conducted a study aimed at investigating the causes of digital hoarding and how it is exacerbated in the hedonic social media context. For this study, 330 valid collected questionnaires were tested. The results show that FOMO significantly positively affects accumulating and difficulty deleting.

Li et al. [31] conducted a study to learn about the relationship between FOMO, smartphone addiction, and social networking site use among a sample of Chinese university students. The item-level network analysis showed that FOMO was positively associated with SNS use and smartphone addiction. There were no significant gender differences in the network structure and the global edge strength. The results showed that excessive social media use and higher levels of FOMO appear to play a contributory role in smartphone addiction. Smartphone addiction may also further increase excessive SNS use and increase the level of FOMO.

Gezgin et al. [32] conducted a study to investigate the relationship between Nomophobia levels of high school students and their Internet Addiction. This study also examines the factors including the duration of smartphone and mobile Internet use that trigger and create this phenomenon. As part of this survey, 929 high school students were randomly selected among 9th to 12th graders from Turkish high schools. Regarding gender differences, female students have a higher tendency to exhibit nomophobic behaviors compared to male students. Additionally, students' grade levels (which could also be considered as age) have no effect on the prevalence of Nomophobia.

Çobanoğlu et al. [33] conducted another study to find out the relationship between nursing students' digital and smartphone addiction levels and Nomophobia. The study was conducted with 215 nursing students in a university located in northeastern Turkey. A positive and moderate correlation was found between students' Nomophobia levels with smartphone addiction and digital addiction levels ($p < 0.05$). Analysis of the regression coefficients determined that smartphone addiction ($\beta = 0.765$; $p < 0.01$) had a significant positive effect on Nomophobia.

Exploring the impact of nomophobic behaviors among hospital nurses on their clinical decision-making perceptions was the purpose of the study by Yang et al. [34]. To achieve that, a descriptive cross-sectional survey design was employed. The nurses from a tertiary hospital in Nanjing in May 2023 were surveyed. Data were gathered using a sociodemographic data form, the Nomophobia Questionnaire, and the Clinical Decision-Making in Nursing Scale. The results showed a robust negative correlation between Nomophobia and clinical decision-making perceptions (r: −0.365, $P<0.001$). This study highlighted that as the degree of Nomophobia intensified, nurses' clinical decision-making perceptions decreased with the increase in Nomophobia.

To find out the association of Nomophobia with Decision Making of Dental Students in Pakistan, a descriptive, cross-sectional study was conducted by Niazi et al. [35]. The level of Nomophobia was determined using the Nomophobia Questionnaire (NMP-Q), and Mobile Phone Problematic Use Scale (MP-PU), and the decision-making skills of dental students were determined using the Melbourne Decision-Making Questionnaire (MDM-Q).

A positive correlation was found between the measure of mobile phone problematic use scale and Nomophobia. Similarly, positive correlations were discovered between Nomophobia and the measure of buck-passing, procrastination, and hypervigilance in regard to decision-making. As for the MDM-Q scale, the procrastination measure had a high correlation with the decision-making value.

To assess the prevalence and correlation of Nomophobia, Phubbing, and social phobia in Portuguese young adults and adults, a study was conducted by Maia and Sousa [36]. 316 subjects, with a mean age of 25.71 years old (SD = 8.231; range 18 - 59) fulfilled a sociodemographic questionnaire, and the Portuguese validations of the Nomophobia Questionnaire, the Phubbing Scale, and the Social Interaction and Performance Anxiety and Avoidance Scale. The results showed a positive, significant correlation between Nomophobia and Phubbing in Portuguese young adults and adults.

2.4. Prediction of Mental Challenges

The study conducted by Rahman et al. [37] presents a data mining and machine learning approach to identify patterns related to Phubbing behavior. The researchers collected data through an online survey of 394 participants and developed multiple models to analyze different aspects of Phubbing, including Phone Obsession (PO), Communication Disturbance (CD), and Partner Phubbing (PP).

The results highlighted that addiction measures fail to predict Phubbing fully. Indeed, Phubbing appeared to be linked in a nonlinear way to both Information and Communication Technology (ICT) measures that do not imply a dysfunctional use of technology and social anxiety. Moreover, the machine learning approach appeared more suitable than traditional linear statistics methods to predict Phubbing, as highlighted by a much higher explained variance.

Another research by Zhang et al. [38] examined hoarding behavior during the COVID-19 pandemic through analysis of social media data. The researchers analyzed hoarding-related tweets from 42,839 unique US Twitter users between March and April 2020, examining patterns of hoarding behavior and anti-hoarding sentiment through multiple analytical approaches including topic modeling. The study found clear demographic patterns in hoarding behavior. The 18-35 age group showed the highest percentage of hoarding behavior at 57.4%, followed by those aged 36-54 at 29.8%, and those over 55 at 12.8%. Regarding gender, females demonstrated higher engagement in both hoarding and anti-hoarding discussions, with 54.4% of hoarding-related tweets coming from female users compared to 45.6% from male users.

Another study was conducted by McKee et al. [39] to figure out the relationship between FOMO and maladaptive behaviors among college students using two complementary analytical approaches. The research was done as a cross-sectional study with 472 college students who completed questionnaires measuring their FOMO levels and various unethical and illegal behaviors. The research found significant relationships between FOMO and various maladaptive behaviors among college students. These behaviors spanned both legal and illegal activities, demonstrating that higher levels of FOMO were associated with an increased likelihood of engaging in problematic behaviors.

Moreover, the models could predict academic misconduct with 87% accuracy, a substantial improvement over the 50% baseline prediction rate.

The machine learning approaches, including logistic regression, random forest, and Support Vector Machine models, consistently showed superior predictive power compared to traditional statistical methods.

Yousha et al. [40] conducted a study to detect cyberbullying on social media using machine learning. They extracted tweets with the Twint Scraping tool via the Twitter API and preprocessed the data by converting text into numerical format with label encoding, splitting it into 80% training and 20% testing sets. The researchers applied the Support Vector Machine (SVM) algorithm to classify tweets as "offensive" or "non-offensive," demonstrating the effectiveness of machine learning in detecting cyberbullying. The study also highlighted the importance of social context and characteristics in identifying online harassment, with the SVM showing promising classification results.

2.5. Clustering and Categorization based on Mental Health Challenges

Liu [41] proposed a psychological management system for college students based on the K-means clustering algorithm. He analyzed mental health data from 1,000 students at a school, using optimized K-means clustering to categorize students into three distinct groups based on their psychological characteristics. The research found that environmental adaptability was the most significant factor affecting students' psychological well-being, and the findings validated the effectiveness of using K-means clustering for analyzing and categorizing student mental health data to provide targeted support and intervention strategies.

Orchard et al. [42] explored how unsupervised clustering methods can identify distinct mental health profiles and corresponding service-use patterns in Ontario, Canada. Four mental health profiles were identified, ranging from clinically diagnosable depression to varying levels of positive mental health and stress. Sociodemographic factors such as age and income were linked to these profiles. Surprisingly, some individuals with moderate mental health accessed services more frequently than those with diagnosable disorders, highlighting a gap between clinical needs and self-perceived needs. The findings emphasized the importance of addressing diverse mental health indicators and tailoring public health strategies to improve mental health outcomes effectively.

Trevithick et al. [43] investigated the alignment between clusters from the Mental Health Clustering Tool (MHCT) and clinical diagnoses among psychiatric in-patients. By analyzing discharge data over a year, this study examines the diagnostic makeup of each cluster and evaluates the clinical utility of the Department of Health's Mental Health Clustering Booklet. The research aimed to improve understanding of the correlation between clustering and diagnoses, ultimately enhancing the accuracy of mental health assessments and optimizing resource allocation in psychiatric services.

Vermeulen-Smit et al. [44] investigated the association between patterns of health risk behaviors (HRBs) and the prevalence of mental disorders. Utilizing latent class analysis, researchers identified distinct clusters of HRBs and examined their correlation with various mental health conditions. The findings revealed a strong association between specific HRB clusters and the presence of mental disorders, underscoring the importance of an integrative approach in preventing mental illnesses. However, due to the study's cross-sectional design, causal relationships between HRB clusters and mental disorders could not be established.

3. Method

The research method consists of six stages, as depicted in Figure 1. In the first stage, we reviewed studies and research exploring mental health challenges in relation to digital technologies. To identify relevant literature on mental health challenges in the digital age, we conducted a structured search across multiple academic databases. To ensure a rigorous and targeted selection of studies, we defined clear inclusion and exclusion criteria.

In the second stage, the identified challenges were systematically integrated and refined to create a comprehensive and cohesive list. This process was carried out by a team of three researchers who conducted an in-depth analysis of numerous studies on mental health challenges. Given the diverse terminology used across the literature, we categorized and standardized the challenges to ensure clarity and consistency. As a result, we developed a structured overview of the most significant mental health challenges, culminating in a finalized list for further analysis.

Stage 3 involves data collection to provide the necessary information for a detailed analysis of the challenges. To collect data, a questionnaire was developed, incorporating mental health-related questions based on the finalized list of challenges identified in the second stage.

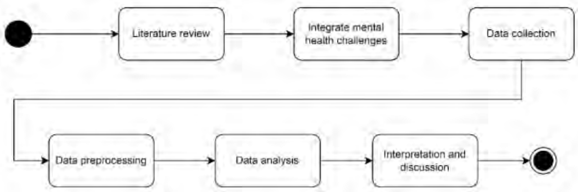

Figure. 1. Research method

Once the data is collected, Stage 4 focuses on preprocessing to prepare the data for analysis including data transformation, feature selection, and data balancing. Stage 5 includes exploratory data analysis (EDA) to gain insights, along with various statistical tests and decision tree analysis for an in-depth examination of mental health challenges. Finally, Stage 6 involves interpreting the results and discussing the findings. Each stage is detailed in the following sub-sections.

3.1. Literature review

We applied a wide range of databases as our primary source, including Google Scholar, Web of Science, Scopus, Springer, Elsevier, Wiley, PubMed. We also added the publications which have cited the extracted records. Records were searched using the following search terms for the title, keywords, and abstract sections.

("Mental" OR "psycholog*" OR "cognit*" OR "emot*" OR "psychiatr*" OR "neurolog*") AND ("health" OR "well-being" OR "wellness" OR "state" OR "condition") AND ("challeng*" OR "disord*" OR "risk" OR "issue*" OR "problem*" OR "difficult*" OR "barrier*" OR "complicat*" OR "vulnerab*" OR "crisis") AND ("digital" OR "online" OR "cyber*" OR "social media" OR "social network*" OR "technolog*" OR "virtual" OR "mobil*" OR "smartphone*" OR "electronic*" OR "comput*") OR ("implicat*" OR "effect*" OR "impact*" OR "consequenc*" OR "outcome*" OR "result*" OR "influenc*")

The main eligibility criteria are as follows.

Inclusion criteria:

- Researches should be written in English.
- Records should be retrieved utilizing the designed search query.
- Studies should be published between January 2010 and April 2024.
- In cases where several papers reported the same study, only the most recent ones were included (i.e., theses and papers extracted from theses, extended versions of papers published in journals).

Exclusion criteria:

- Studies not related to research questions are ignored.
- Article is written in non-English.
- Non-peer-reviewed sources which include non-peer-reviewed articles, opinion pieces, and non-scholarly sources are excluded to ensure the reliability and credibility of our research.
- papers that do not specifically address the intersection of mental health and digital technology (e.g., studies focusing solely on physical health or unrelated social issues) are also excluded.

3.2. Integrate Mental Health Challenges

In our review, we conducted a thorough analysis of numerous studies addressing mental health challenges proposed by various researchers. Our team of three researchers embarked on a systematic process of retrieving, reviewing, and analyzing these studies to form a comprehensive and cohesive list of the challenges.

Initially, we identified a wide array of mental health challenges, often referred to by different terminologies across the studies. To address this variability, we engaged in several collaborative brainstorming sessions. These discussions were supported by the use of mind mapping tools, which helped us to organize and visualize the key themes emerging from the literature. Through this process, we distilled the core challenges into a set of unified categories, assigning standardized names to each challenge to ensure consistency and clarity. By synthesizing these findings, we present a structured overview of the most significant mental health challenges.

3.3. Data Collection

To collect data, a questionnaire was developed that included demographic questions (Gender, Age, Education, and Job), Online time, and 15 questions related to mental challenges. Three experts collaborated to create the questionnaire through brainstorming sessions. Each item was then tested by users to ensure that they were understandable, readable, and credible. The test users provided feedback on the items, and the questionnaire was refined iteratively by the three experts.

Once finalized, the questionnaire was created online using the Porsline survey tool. Two workshops were held to educate participants about mental challenges, after which they were asked to complete the questionnaire. Additionally, the questionnaire and instructions for completion were sent to participants through the Telegram social messaging app. Participants willingly consented to complete the questionnaire as part of this research study. The privacy and security of our respondents were of paramount importance, and all necessary measures were taken to protect their personal information.

3.4. Data Preprocessing

Since the data collected is based on a Likert scale, normalization is not necessary due to its ordinal nature. We have not handled missing value because imputing missing values in a Likert scale questionnaire may introduce bias and distort the data's integrity. Likert scale responses are ordinal in nature, meaning they represent ordered categories rather than continuous data. Imputation techniques, particularly those designed for continuous data (like mean or regression imputation), can artificially inflate relationships between variables or obscure the true variability in responses.

For proportion analysis and exploring relationships between variables using the Decision Tree algorithm, we transformed the 5-point Likert scale into binary values. Two methods were tested to determine the optimal transformation. The first method categorized responses of 1 and 2 as 'Low' and 3, 4, and 5 as 'High.' The second method grouped 1, 2, and 3 as 'Low' and 4 and 5 as 'High.' The first method proved more effective, leading to better analytical results.

Since some 5-point Likert items in the questionnaire were reverse-coded, their scores were subtracted from 6 to ensure consistency across all responses.

We employed CFS (Correlation-based Feature Selection) due to its recently demonstrated effectiveness in enhancing machine learning performance [45]. CFS evaluates the worth of a subset of features by considering both the individual predictive ability of each feature and the degree of redundancy between them. The idea behind CFS is that good feature subsets contain features that are highly correlated with the class label (i.e., predictive of the target) and uncorrelated with each other (i.e., not redundant).

In cases where the class imbalance ratio exceeded 4:1, the dataset was balanced using both SMOTE over-sampling and random under-sampling techniques. However, over-sampling resulted in overfitting and produced overly complex models. As a result, the under-sampling method with a 1:1 class distribution was chosen as the preferred approach for handling imbalanced data.

3.5. Data Analysis

To analyze the data, we first report descriptive statistics, including the mean, percentage, standard deviation, and frequency. An independent t-test and a 95% confidence interval were employed to compare the mean differences of each mental challenge with respect to age and gender as categorical variables. To analyze proportions, we applied a one-sample proportion confidence interval using the Wilson score method. Pearson correlation analysis with a 95% confidence level was also employed to examine the relationships between mental health challenges. To examine the relationships among multiple variables, we applied a decision tree classifier, treating each mental challenge as a target variable while using the remaining challenges as input features. The decision tree method was chosen because it is a highly interpretable and explainable algorithm, making it easy to understand, while also being effective for classifying instances with nominal features. 10-fold cross-validation is used to evaluate each classification model. This approach allows us to identify non-linear relationships between the various mental challenges. Finally, cluster analysis using the K-means method was conducted to segment individuals based on prevalent mental health challenges.

The integration of statistical tests, correlation analysis, decision tree analysis, and clustering in this study serves distinct but complementary objectives, ensuring a comprehensive understanding of mental health challenges in the digital age.

Statistical tests, such as t-tests and proportion analyses, were employed to validate significant differences in mental health challenges across demographic groups (e.g., age, gender) and identify key prevalence patterns.

Correlation analysis was conducted to uncover linear relationships between different mental health challenges. These correlations offered insight into how challenges co-occur, underscoring the interconnected nature of mental health stressors in the digital context.

The decision tree analysis further explored non-linear and deeper relationships among challenges, identifying specific predictive rules.

Finally, clustering was employed to segment the population into distinct groups based on shared mental health profiles, such as those experiencing severe versus mild challenges. This segmentation enables the tailoring of interventions to address the needs of specific subgroups effectively.

3.6. Interpretation and Discussion

Using an independent t-test allows us to compare the mean differences in mental health challenges between males and females, as well as between individuals aged less than 18 and those over 18 years. This statistical analysis helps identify significant gender and age-related disparities in mental health issues.

Following this, a proportion analysis is conducted to rank the mental challenges based on their prevalence, highlighting the importance of each challenge in the population. Subsequently, the results of correlation analysis are interpreted to determine which mental challenges are significantly correlated, shedding light on potential relationships between different issues.

After applying a decision tree analysis, we interpret the derived rules to explore meaningful relationships within the data. Finally, the segments identified through cluster analysis are examined to develop a comprehensive model of the mental health landscape in the population, providing insights into distinct groups and their unique challenges.

4. Results

4.1. Mental Health Challenges

After reviewing, studying, and synthesizing the literature on mental health challenges, 15 key challenges were identified in response to **RQ1**, as follows:

1. Social media pressure
2. Cyberbullying
3. FOMO
4. Impaired emotional and social intelligence
5. ADHD
6. Social isolation
7. Memory decline
8. Crisis exposure
9. Pressures on parenting
10. Engaging with inappropriate content online
11. Nomophobia
12. TAD
13. Decision-making and analytical thinking loss
14. Phubbing
15. Hoarding

The analysis revealed varying levels of research attention across different challenges. Social media pressure, cyberbullying, and social isolation emerged as extensively studied areas, each supported by five distinct research papers. Similarly, Phubbing received substantial attention with five studies examining its impacts. FOMO, ADHD, memory decline, parenting pressures, Nomophobia, and TAD were each analyzed through four separate studies, providing robust evidence bases for these challenges. Impaired emotional and social intelligence and analytical thinking were each examined through three studies, as was hoarding behavior. Engagement with inappropriate online content and Crisis exposure were investigated in two research papers. distribution of research attention highlights both well-studied areas and potential gaps in the literature regarding digital-age mental health challenges, suggesting opportunities for future research particularly in less-examined areas such as crisis exposure and engagement with inappropriate content.

The temporal distribution of research articles addressing the fifteen identified mental health challenges reveals an evolving scholarly focus over nearly three decades. The earliest relevant research emerged in 1996, followed by sporadic publications in 2003, 2004, and 2008. A notable increase in research attention began in 2010 with three publications, followed by two articles in 2012. The years 2013 and 2016 marked significant peaks in research output, each producing six articles. The period between 2017 and 2022 maintained consistent scholarly interest, with annual publications ranging from four to seven articles, reaching its highest output in 2022 with seven publications. Recent years have shown a moderated but continued interest, with two articles each in 2023 and early 2024. This publication pattern demonstrates an overall increasing trend in research attention to digital-age mental health challenges since 2010, with particularly robust scholarly activity in the 2013-2022 period.

Social media pressure**:** Social media has created significant pressure, especially for young people, by exposing them to idealized portrayals of life that lead to harmful comparisons and feelings of inadequacy, anxiety, and depression. Studies, including one by Primack et al., highlight that exposure to these curated images increases body dissatisfaction and depressive symptoms among adolescents [46]. This constant comparison fosters negative self-evaluation and emotional distress, contributing to issues like body image concerns and disordered eating behaviors [47]. The phenomenon of "Facebook envy" further exacerbates feelings of loneliness and depression as individuals perceive others as happier and more successful [48]. Additionally, frequent use of visually-driven platforms like Instagram is linked to increased depressive symptoms, particularly when users engage in social comparison [49].

Cyberbullying: Cyberbullying has emerged as a widespread issue in the digital age, particularly affecting adolescents and young adults through technology, making it a constant threat compared to traditional bullying [50]. The anonymity of online platforms allows perpetrators to harass victims more intensely without immediate consequences, leading to various forms of abuse, including harassment, doxing, and public shaming [51]. Victims often suffer severe emotional trauma, including anxiety, depression, and in extreme cases, suicidal ideation [52]. The relentless nature of cyberbullying can result in poor academic performance and long-term mental health issues [53]. Additionally, it creates a toxic digital environment that discourages safety and encourages further bullying behaviors among users [54].

Fear of Missing Out (FOMO)**:** FOMO has become increasingly common in the digital age, particularly due to social media, where it manifests as anxiety over missing rewarding experiences others are having. This phenomenon drives individuals to compulsively check social media updates, leading to emotional distress, reduced life satisfaction, and interference with daily activities and social interactions [55]. Recent studies highlight FOMO's significant influence on internet addiction among adolescents, with individuals exhibiting higher FOMO levels engaging in excessive internet use to cope with their feelings of exclusion [56]. This behavior correlates with increased stress, anxiety, and depression [57]. A meta-analysis confirms that FOMO is consistently linked to problematic internet behaviors across various age groups and cultures, emphasizing its global significance [5].

***Impaired emotional and social intelligence*:** in the digital age, excessive screen-based media use has significantly impacted communication, particularly among young people, by reducing face-to-face interactions essential for developing emotional and social intelligence. A five-day screen-free camp demonstrated that participants better recognized emotional signals compared to those who used digital media [58]. Turkle [59] discusses the phenomenon of "being alone together," where individuals are physically present but engaged with devices, leading to weakened interpersonal skills and reduced empathy. Furthermore, Twenge and Campbell [60], link the rise in mental health issues among adolescents, such as anxiety and depression, to decreased face-to-face interactions, suggesting that increased screen time correlates with diminished opportunities for emotional and social development.

***Attention Deficit and Hyperactivity Disorder (ADHD)*:** ADHD is marked by patterns of inattention, hyperactivity, and impulsivity, and recent research suggests that excessive screen time may exacerbate these symptoms. Adolescents with high electronic media use show more pronounced ADHD symptoms, likely due to the fast-paced, attention-demanding nature of digital media [61]. A study found a significant link between early childhood television viewing and later attention problems, indicating that rapid scene changes may hinder the developing brain's ability to focus [62]. A meta-analysis confirmed a modest but significant association between media use and attention issues, noting that interactive media, like video games, have a greater impact than passive media [63]. Additional research highlights that increased screen time correlates with higher hyperactivity and impulsivity, while excessive media use disrupts sleep, limits physical activity, and contributes to various cognitive and behavioral problems, including ADHD [64].

Social isolation: Social disconnection, characterized by a lack of meaningful relationships and belonging, significantly impacts mental and physical health, leading to issues like depression, anxiety, and increased mortality risk. A study by Primack et al. [46] found that individuals spending over two hours daily on social media were more likely to feel socially isolated, a trend consistent across various age groups. This disconnection may arise from the idealized portrayals on social media, prompting unfavorable comparisons that foster feelings of inadequacy. Additional research indicates that passive consumption of social media content exacerbates feelings of loneliness, while poor sleep quality from late-night usage further impairs social interactions [65][66]. Experimental evidence shows that a week-long break from Facebook led to lower perceived isolation and higher life satisfaction [67]. Furthermore, Shakya and Christakis [68] demonstrated that increased social media use correlates with decreased real-life interactions and heightened feelings of isolation over time, highlighting the displacement of genuine social connections.

Memory decline: The rising prevalence of screen usage in the digital age raises concerns about its detrimental effects on cognitive functions, particularly memory. Excessive screen time is linked to declines in both short-term and long-term memory, affecting academic performance, self-esteem, and overall mental well-being [69]. Prolonged exposure to digital devices disrupts the brain's ability to process and retain information, largely due to constant attention switching and information overload, which fragments focus and hampers tasks requiring sustained concentration [70]. Long-term memory is also negatively impacted, as high screen engagement reduces time spent on activities that promote memory consolidation, while blue light exposure disrupts sleep critical for cognitive function [71]. Additionally, Hamer and Stamatakis [72] found that high screen time correlates with cognitive decline in older adults, indicating that the adverse effects of screen time extend beyond youth to affect all age groups.

***Crisis exposure*:** In the digital age, rapid dissemination of news via social media and apps exposes young people to a constant stream of distressing events, such as natural disasters and political crises, leading to information overload. Rosen et al. [73] discuss "compassion fatigue," an emotional exhaustion resulting from repeated exposure to such news, which diminishes empathy and fosters detachment, negatively affecting mental well-being. Similarly, Twenge et al. [60] found that excessive screen time, particularly for news consumption, correlates with increased anxiety and depressive symptoms among adolescents, suggesting that the negative content encountered online heightens feelings of fear and uncertainty.

***Pressures on parenting*:** In the digital era, parenting faces multifaceted challenges that significantly impact parents' mental well-being, primarily due to constant connectivity and evolving expectations. A major source of stress is ensuring children's online safety, as parents grapple with the need to monitor digital activities while fostering their independence, leading to pervasive anxiety [74]. Social media compounds this pressure by providing a platform for connection but also exposing parents to idealized family portrayals that fuel feelings of inadequacy and increased parenting stress [75]. Additionally, parents struggle to set screen time boundaries for their children, as highlighted by Wartella et al. [76], and are expected to be tech-savvy to navigate new digital trends, creating further overwhelm, particularly for those less familiar with technology [77].

***Engaging with inappropriate content online*:** Engagement with inappropriate online content poses a significant issue in the digital age, especially as children and adolescents gain widespread internet access. Exposure to harmful materials—such as violence, explicit content, and cyberbullying—can lead to serious psychological effects, including anxiety, depression, and distorted perceptions of reality. Research shows that frequent encounters with such content may desensitize youth to violence and normalize risky behaviors [78]. The anonymity of the internet allows harmful interactions to flourish without immediate consequences, worsening the issue. Addressing this challenge is vital for creating a safer digital environment, as it affects not only the emotional and social development of young users but also societal norms and behaviors [79].

***Nomophobia*:** Nomophobia or the fear and anxiety experienced when individuals cannot use or be reached by their mobile phones, has become increasingly prevalent as smartphone usage rises, with estimates of affected individuals ranging from 39.5% to 42.6%. This dependency is linked to certain personality traits, such as low self-esteem and high extraversion, which can predict the likelihood of experiencing Nomophobia [80]. The COVID-19 pandemic worsened this issue among students engaged in online learning, as many reported significant discomfort and anxiety when unable to access their devices [81]. Additionally, the immediate gratification provided by smartphones can undermine impulse control, making it difficult to resist checking devices frequently [82]. Social media also plays a role, as its emphasis on real-time connectivity can heighten the FOMO, leading to increased Nomophobia among users [32].

Technology Addiction Disorders (TAD): Continuous engagement in video games can lead to Technology Addiction Disorders [83], influenced by individual personality traits that affect gaming choices and behaviors. Chassiakos and Stager [82] discuss Problematic Internet Use (PIU), characterized by an inability to control internet usage, which often results in negative life consequences and shares similarities with other addictive behaviors. Research indicates that PIU predicts poor sleep quality, directly and indirectly through mental health issues like depression and anxiety, particularly among medical students [84]. A systematic review highlights the association between PIU and mental health challenges in children, underscoring the need for comprehensive intervention strategies that include parental involvement, school programs, and psychological therapies to address PIU and its related mental health issues [85].

***Analytical Thinking and Decision-making loss*:** Concerns about internet use suggest it may promote superficial thinking, as the vast availability of information reduces the need for engaging in complex cognitive processes. Research indicates that individuals within interconnected networks, like the Internet, are less likely to employ necessary cognitive strategies when solutions are easily accessible [86]. Additionally, constant exposure to the idealized lifestyles of social media influencers can lead to negative emotions and depression through social comparison and technostress, further challenging cognitive and analytical abilities [87]. The rise of AI technologies in sectors like education may also diminish human decision-making and critical thinking skills by fostering reliance on automated systems [88]. Furthermore, algorithmic bias in AI can exacerbate decision-making issues, particularly affecting marginalized communities, while high daily phone usage and constant notifications contribute to digital overload, impeding cognitive processing and decision-making [89] [90].

Hoarding: Hoarding disorder is characterized by five diagnostic criteria: persistent difficulty discarding possessions regardless of their value; a strong urge to save items, accompanied by distress when considering disposal; accumulation of clutter that severely compromises living space; clinically significant distress or impairment in daily functioning; and symptoms not better explained by another medical or psychiatric condition [91]. The cognitive-behavioral model, initially conceptualized by Frost and Hartl and later refined by Steketee and Frost [92] [93], offers a comprehensive understanding of the factors contributing to the vulnerability and maintenance of hoarding behaviors.

Phubbing: This term describes the phenomenon of individuals becoming so preoccupied with their devices that they neglect face-to-face interactions and social connections, often viewed as a manifestation of internet and smartphone addiction [94]. It is particularly prevalent among younger generations, such as adolescents and young adults, who heavily rely on smartphones and social media [95].

Phubbing is associated with increased levels of depression, anxiety, stress, and other psychological distress in both the perpetrators and victims [96]. It can lead to emotional and social disengagement, loneliness, and lower self-concept clarity [97]. Phubbing can also negatively impact the quality of social interactions, reducing empathy, trust, and relationship satisfaction, particularly in friendships and romantic relationships [96]. Additionally, the COVID-19 pandemic and increased digital education may have exacerbated the negative impacts of Phubbing on mental health and well-being [98].

4.2. Data analysis

Descriptive Statistics

The participation rate is 74%, indicating that 26% of participants started the questionnaire but did not complete it. The average completion time for the questionnaire is 16 minutes and 55 seconds, with 555 participants completing it. A majority, 92%, of participants used smartphones to respond, followed by 7% who used desktop computers and 1% who used tablets.

Of the participants, 74.6% are female, 22.2% are male, and 3.2% prefer not to disclose their gender. The average age is 30.51 years for females and 36.38 years for males. Daily digital technology usage is distributed as follows: 30 participants use it for less than 1 hour, 190 for 1–3 hours, 153 for 3–5 hours, 88 for 5–8 hours, and 88 for more than 8 hours. Regarding education, most participants are students, who have a bachelor's degree, or a master's degree.

In the next step, mental health challenges were analyzed based on participants' age and gender. For age, individuals were divided into two groups: those below 18 years old and those above 18 years old, to examine the results for each group. Table 1 shows the results of the t-test for comparing mean differences between each group corresponding to each mental health challenge. It is noteworthy that only those mean differences with a Sig. (2-tailed) values equal to or less than 0.06 are included in this table.

Table 2 shows the results for the mental health challenges of the two groups of individuals from Table 1. As shown in Table 2, the values for mean of mental challenges are higher for individuals over 18 years old. It is worth mentioning that although "Hour" is not specifically related to a mental challenge, it has been included in this table as it facilitates better and easier analysis of the results.

Table 2 shows the results for the mental health challenges of the two groups of individuals from Table 1. As shown in Table 2, the values for mean of mental challenges are higher for individuals over 18 years old. It is worth mentioning that although "Hour" is not specifically related to a mental challenge, it has been included in this table as it facilitates better and easier analysis of the results.
Table 2 illustrates that participants aged over 18 have invested significantly more time in using digital technologies than their counterparts under 18. The findings demonstrate statistically significant differences across 6 mental health challenges, with older individuals consistently reporting higher mean values. These results are noteworthy as they highlight age-specific vulnerabilities. The broader implications of these trends suggest the necessity for age-targeted interventions that address unique stressors associated with adulthood. Validation of these findings is supported by narrow confidence intervals and low standard errors, which indicate high precision in the estimated differences.

Next, individuals were divided into two groups based on their gender, and all the procedures mentioned above were performed for these two groups as well. The results are shown in Tables 3 and 4. As indicated in Table 3, the values for all mental challenges are higher for males than for females. As shown in Table 4, the mean differences for 4 mental health challenges are statistically significant, with males consistently having higher mean values than females for all of these challenges.

As shown in Table 4, the mean differences for 8 mental health challenges are statistically significant, with males consistently having higher mean values than females for all of these challenges. The practical relevance of these results highlights the necessity for gender-specific strategies in addressing digital-age mental health challenges. Validation of the statistical results is evident from the robust test statistics and low standard errors.

In response to RQ2, regarding Hours, Memory_Decline, Crisis_Exposure, Inappropriate Content, Nomophobia, TAD, and Pressures Parenting, the difference in means between age groups is statistically significant and for all these variables the mean values are higher for individuals aged ≥18 compared to those under 18. This suggests that adults experience higher levels of these mental challenges.

Pressures of parenting shows a particularly large difference in means (3.46 for ≥18 vs. 2.62 for <18), likely because parenting is more common among adults. Inappropriate content and Memory decline also show notable differences, indicating higher exposure and more memory issues in the adults. Regarding Hours, individuals aged ≥18 spend more time (3.25 hours on average) compared to those under 18 (2.60 hours).

Regarding Hours, Nomophobia FOMO, Crisis_Exposure, Pressures_Parenting, Inappropriate Content, TAD, Hoarding, and Phubbing, the difference in means between gender groups is statistically significant. For all variables, males show

Table 1. Independent samples test for age (≥ 18 and < 18)

t-test for Equality of Means						
	Condition	***Sig. (2-tailed)***	***Mean Difference***	***Std. Error Difference***	***95% Confidence Interval of the Difference***	
					Lower	***Upper***
Hours	Equal variances assumed	0.000	0.651	0.104	0.447	0.854
	Equal variances not assumed	0.000	0.651	0.098	0.459	0.842
Memory_Decline	Equal variances assumed	0.003	0.349	0.115	0.123	0.574
	Equal variances not assumed	0.003	0.349	0.115	0.121	0.576
Crisis_Exposure	Equal variances assumed	0.000	0.818	0.131	0.560	1.076
	Equal variances not assumed	0.000	0.818	0.128	0.567	1.069
Pressures_parenting	Equal variances assumed	0.000	0.843	0.126	0.595	1.090
	Equal variances not assumed	0.000	0.843	0.130	0.587	1.098
Inappropriate_Content	Equal variances assumed	0.000	0.874	0.124	0.631	1.117
	Equal variances not assumed	0.000	0.874	0.125	0.628	1.120
Nomophobia	Equal variances assumed	0.060	0.235	0.125	-0.010	0.479
	Equal variances not assumed	0.065	0.235	0.127	-0.015	0.484
TAD	Equal variances assumed	0.027	0.275	0.124	0.031	0.518
	Equal variances not assumed	0.028	0.275	0.124	0.030	0.519

higher mean values than females. For instance, the mean difference for Hours is -0.673, indicating that males report spending significantly more time than females. For Inappropriate Content, the mean difference is -0.838, showing a higher exposure to inappropriate content for males compared to females.

Proportion Analysis

The proportion of individuals experiencing mental challenges has been illustrated in Table 5. These proportions show the percentage of individuals for whom the corresponding factor is categorized as High. As the results indicate, the maximum standard error is 0.021, leading to a very narrow confidence interval for the proportions.

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In response to **RQ3**, Figure 2 presents the prevalence of mental health challenges among participants as percentages. The most common challenge is Pressure of Parenting, followed by Hoarding and Exposure to Inappropriate Content. These findings are validated by narrow confidence intervals, with the maximum standard error observed being 0.021.

Correlation Analysis

In this section, the correlations between mental health challenges were calculated, and those with a Pearson coefficient greater than 0.4 are as follows.

- SM_Pressure and Social_Isolation: r = 0.402, $p < 0.001$,
- N = 544
- SM_Pressure and DM_Loss: r = 0.416, $p < 0.001$, N = 545
- FOMO and Nomophobia: r = 0.475, $p < 0.001$, N = 540
- FOMO and TAD: r = 0.508, $p < 0.001$, N = 541
- Crisis_Exposure and Inappropriate_Content: r = 0.415,
- $p < 0.001$, N = 542
- Nomophobia and TAD: r = 0.682, $p < 0.001$, N = 541
- Nomophobia and DM-Loss: r = 0.416, $p < 0.001$, N = 543
- Nomophobia and Phubbing: r = 0.483, $p < 0.001$, N = 543
- TAD and DM-Loss: r = 0.412, $p < 0.001$, N = 542
- TAD and Phubbing: r = 0.402, $p < 0.001$, N = 542

The correlation analysis highlights significant relationships between various mental health challenges, such as the strong correlation between Nomophobia and TAD (r = 0.682, $p < 0.001$). These findings are consistent with theoretical models that emphasize the co-occurrence of digital-age stressors. For example, FOMO's correlation with both TAD (r = 0.508) and Nomophobia (r = 0.475) underscores its central role in amplifying mental health vulnerabilities.

Validation of these relationships is demonstrated through the statistical significance of the correlation coefficients and the large sample sizes used in the analysis (e.g., N = 541 for Nomophobia and TAD).

In response to **RQ4**, Nomophobia is correlated with TAD, DM_Loss, Phubbing, and FOMO. Moreover, TAD is correlated with DM_Loss, Phubbing, and FOMO. Social-Pressure is correlated with Social-Isolation and DM-Loss. Finally, Crisis_Exposure is correlated with Inappropriate_Content.

Figure. 2. Prevalence of mental health challenges among participants (as a Percentage)

Table 2. Group statistics for age

	Age	*N*	*Mean*	*Std. Deviation*	*Std. Error Mean*
Hours	≥ 18	363	3.25	1.185	0.062
	< 18	175	2.60	0.994	0.075
Memory_Decline	≥ 18	360	2.31	1.241	0.065
	< 18	174	1.96	1.256	0.095
Crisis_Exposure	≥ 18	360	2.97	1.460	0.077
	< 18	175	2.15	1.348	0.102
Pressures_Parenting	≥ 18	355	3.46	1.315	0.070
	< 18	172	2.62	1.436	0.110
Inappropriate_Content	≥ 18	358	2.99	1.322	0.070
	< 18	174	2.12	1.369	0.104
Nomophobia	≥ 18	359	2.54	1.330	0.070
	< 18	175	2.31	1.397	0.106
TAD	≥ 18	360	2.45	1.334	0.070
	< 18	174	2.18	1.355	0.103

Table 3. Independent samples test for gender

t-test for Equality of Means						
	Condition	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
					Lower	Upper
Hours	Equal variances assumed	0.000	-0.673	0.117	-0.902	-0.444
	Equal variances not assumed	0.000	-0.673	0.120	-0.909	-0.437
FOMO	Equal variances assumed	0.007	-0.371	0.137	-0.641	-0.101
	Equal variances not assumed	0.006	-0.371	0.133	-0.634	-0.108
Crisis_Exposure	Equal variances assumed	0.001	-0.488	0.151	-0.784	-0.192
	Equal variances not assumed	0.001	-0.488	0.148	-0.780	-0.196
Pressures_Parenting	Equal variances assumed	0.045	-0.295	0.147	-0.584	-0.006
	Equal variances not assumed	0.040	-0.295	0.140	-0.577	-0.013
Inappropriate_Content	Equal variances assumed	0.000	-0.838	0.137	-1.114	-0.562
	Equal variances not assumed	0.000	-0.838	0.125	-1.107	-0.569
Nomophobia	Equal variances assumed	0.053	-0.272	0.140	-0.547	0.003
	Equal variances not assumed	0.058	-0.272	0.142	-0.552	0.009
TAD	Equal variances assumed	0.000	-0.553	0.136	-0.819	-0.286
	Equal variances not assumed	0.000	-0.553	0.139	-0.827	-0.278
Hoarding	Equal variances assumed	0.048	-0.285	0.144	-0.569	-0.002
	Equal variances not assumed	0.046	-0.285	0.142	-0.565	-0.005
Phubbing	Equal variances assumed	0.002	-0.363	0.119	-0.597	-0.130
	Equal variances not assumed	0.005	-0.363	0.127	-0.614	-0.112

Classification

To extract the relationships between mental health challenges, we used a decision tree learning algorithm to predict a specific mental challenge based on others. This approach helps uncover complex, non-linear relationships. Figure 3 shows the F-Measure values of prediction models. Notably, for TAD, the decision tree was trivial: if Nomophobia is High, TAD is also High, and if Nomophobia is Low, TAD is Low. Therefore, we removed Nomophobia and relearned the decision tree to discover other meaningful rules.

Further addressing **RQ4**, the following rules predict the mental challenges as High:

Pressures of Parenting

Rule 1: If (Inappropriate_Content = High)

Rule 2: If (Inappropriate_Content = Low AND Crisis_Exposure = High)

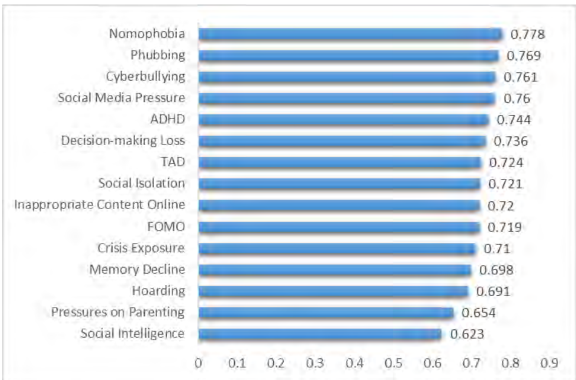

Figure. 3. F-Measure of decision tree models in predicting mental health challenges

Hoarding

Rule 1: If (DM_Loss = High)

Rule 2: If (DM_Loss = Low AND Nomophobia = High)

Rule 3: If (DM_Loss = Low AND Nomophobia = Low AND TAD = High AND Crisis_ Exposure = High)

Rule 4: If (DM_Loss = Low AND Nomophobia = Low AND TAD = Low AND FOMO = High AND Memory_Decline = High)

Rule 5: If (DM_Loss = Low AND Nomophobia = Low AND TAD = Low AND FOMO = High AND Memory_Decline = Low AND Crisis_Exposure = High)

Inappropriate Content

Rule 1: If (Crisis_Exposure = Low AND Pressures_parenting = High AND Nomophobia = High)

Rule 2: If (Crisis_Exposure = Low AND Pressures_parenting = High AND Nomophobia = Low AND FOMO = High AND TAD = High)

Rule 3: If (Crisis_Exposure = High AND TAD = High)

Rule 4: If (Crisis_Exposure = High AND TAD = Low AND Pressures_parenting = High)

Crisis Exposure

Rule 1: If (Inappropriate_Content = Low AND DM_Loss = High AND Pressures_parenting = High)

Rule 2: If (Inappropriate_Content = Low AND DM_Loss = High AND Pressures_parenting = Low AND FOMO = High AND SM_Pressure = High)

Rule 3: If (Inappropriate_Content = High AND Memory_Decline = High)

Rule 4: If (Inappropriate_Content = High AND Memory_Decline = Low AND Social_Isolation = High AND FOMO = High)

Rule 5: If (Inappropriate_Content = High AND Memory_Decline = Low AND Social_Isolation = Low AND Nomophobia = High)

Rule 6: If (Inappropriate_Content = High AND Memory_Decline = Low AND Social_Isolation = High AND FOMO = Low AND Pressures_parenting = High AND SM_Pressure = Low)

TAD

Rule 1: If (Nomophobia = High)

Rule 2: If (FOMO = High AND DM_Loss = High)

Rule 3: If (FOMO = High AND DM_Loss = Low AND Social_Isolation = High)

FOMO

Rule 1: If (TAD = High AND Phubbing = High AND Crisis_Exposure = High)

Rule 2: If (TAD = High AND Phubbing = High AND Crisis_Exposure = Low AND Memory_Decline = High)

Rule 3: If (TAD = High AND Phubbing = Low AND Social_Intelligence = Low AND Nomophobia = High)

Rule 4: If (TAD = High AND Phubbing = High AND Crisis_Exposure = Low AND Memory_Decline = Low AND Social_Intelligence = Low AND Nomophobia = Low)

Rule 5: If (TAD = High AND Phubbing = High AND Crisis_Exposure = Low AND Memory_Decline = Low AND Social_Intelligence = Low AND Nomophobia = High AND Inappropriate_Content = High)

Rule 6: If (TAD = High AND Phubbing = High AND Crisis_Exposure = Low AND Memory_Decline = Low AND Social_Intelligence = Low AND Nomophobia = High AND Inappropriate_Content = Low)

Social Isolation

Rule 1: If (ADHD = Low AND SM_Pressure = High AND DM_Loss = High)

Rule 2: If (ADHD = Low AND SM_Pressure = High AND DM_Loss = Low AND TAD = High AND Crisis_Exposure = High)

Rule 3: If (ADHD = High AND Cyberbullying = High)

Rule 4: If (ADHD = High AND Cyberbullying = Low AND Crisis_Exposure = High)

Rule 5: If (ADHD = High AND Cyberbullying = Low AND Crisis_Exposure = Low AND SM_Pressure = High)

Memory Decline

Rule 1: If (ADHD = Low AND Nomophobia = Low AND Social_Isolation = High AND TAD = High AND FOMO = Low)

Rule 2: If (ADHD = Low AND Nomophobia = High AND DM_Loss = High AND Crisis_Exposure = High AND FOMO = High AND Social_Isolation = High)

Rule 3: If (ADHD = Low AND Nomophobia = High AND DM_Loss = High AND Crisis_Exposure = High AND FOMO = Low AND Social_Isolation = High)

Rule 4: If (ADHD = High AND Crisis_Exposure = High)

Rule 5: If (ADHD = High AND Crisis_Exposure = Low AND FOMO = High)

Decision Making Loss

Rule 1: If (SM_Pressure = High AND Phubbing = High)

Rule 2: If (SM_Pressure = High AND Phubbing = Low AND Cyberbullying = High)

Rule 3: If (SM_Pressure = High AND Phubbing = Low AND Cyberbullying = Low AND ADHD = Low AND Hoarding = High)

Rule 4: If (SM_Pressure = Low AND Hoarding = High AND ADHD = High AND TAD = High)

Rule 5: If (SM_Pressure = Low AND Hoarding = Low AND Nomophobia = High AND ADHD = High)

Rule 6: If (SM_Pressure = Low AND Hoarding = High AND ADHD = Low AND Social_Isolation = High AND Crisis_Exposure = High)

Rule 7: If (SM_Pressure = Low AND Hoarding = Low AND Nomophobia = High AND ADHD = Low AND TAD = High AND Phubbing = High)

Rule 8: If (SM_Pressure = Low AND Hoarding = Low AND Nomophobia = High AND ADHD = Low AND TAD = High AND Phubbing = Low AND Crisis_Exposure = High)

Social Intelligence

Rule 1: If (Pressures_parenting = Low AND FOMO = Low AND Cyberbullying = Low)

Phubbing

Rule 1: If (Nomophobia = High AND DM_Loss = High AND FOMO = High)

Rule 2: If (Nomophobia = High AND DM_Loss = High AND FOMO = Low AND TAD = Low)

Social Media Pressure

Rule 1: If (DM_Loss = High AND Cyberbullying = Low AND Crisis_Exposure = High AND Social_Isolation = High)

Rule 2: If (DM_Loss = High AND Cyberbullying = High AND Nomophobia = High)

ADHD

Rule 1: If (Memory_Decline = Low AND DM_Loss = High AND Phubbing = High)

Rule 2: If (Memory_Decline = Low AND DM_Loss = High AND Phubbing = Low AND Social_Isolation = High)

Rule 3: If (Memory_Decline = High AND Hoarding = High AND FOMO = High)

Rule 4: If (Memory_Decline = High AND Hoarding = High AND FOMO = Low AND SM_Pressure = High)

Rule 5: If (Memory_Decline = High AND Hoarding = Low)

Cyberbullying

Rule 1: If (TAD = High)

The decision tree analysis in the study revealed several significant findings. One key outcome was the consistent prediction of TAD by high levels of Nomophobia, demonstrating a clear dependency between these factors. For pressures related to parenting, the analysis identified that high exposure to inappropriate content was a primary predictor, while high levels of crisis exposure emerged as a secondary predictor in the absence of inappropriate content exposure.

Hoarding behavior was another area where decision tree analysis provided valuable insights. High decision-making loss (DM_Loss) was identified as the strongest predictor, while combinations of other challenges, such as TAD, crisis exposure, and FOMO, refined the predictions further. Similarly, for exposure to inappropriate content, the analysis highlighted that high crisis exposure combined with TAD was a strong predictor, while in cases of low crisis exposure, pressures related to parenting and Nomophobia became significant factors.

The findings also revealed complex patterns for FOMO and crisis exposure. High FOMO, combined with challenges such as TAD, Phubbing, and memory decline, increased vulnerability to crisis exposure. Social isolation was strongly predicted by high levels of social media pressure and decision-making loss, while high ADHD or experiences of cyberbullying also significantly contributed to social isolation.

These findings emphasize the intricate relationships among digital-age mental health challenges, demonstrating how overlapping factors interact to exacerbate individuals' vulnerabilities. By uncovering specific predictive rules, the decision tree analysis offers actionable insights that can guide the design of tailored interventions to address co-occurring mental health challenges effectively.

Clustering/Segmentation

In this section, we present the results of clustering participants into four segments using the K-means algorithm. Cyberbullying and ADHD were excluded from clustering due to their prevalence being less than 20%. Table 6 shows the four resulting clusters.

Figure 4 presents the average value of each mental health challenge across the clusters.

In response to **RQ5**, Cluster MC2, with an average score of 3.5, represents individuals experiencing severe mental health challenges, accounting for 21% of the population. Clusters MC1 and MC4, with average scores of 2.46 and 2.49 respectively, represent individuals with mild mental health challenges and together make up 44% of the tested sample. Finally, 35% of individuals belong to Cluster MC3, which has the lowest average score of 1.77 for mental health challenges.

4.3. Discussion

Research by Pritam & Sarbil [24] demonstrated a higher prevalence of nomophobia and TAD among males, which aligns with our gender-based analysis. Their study also found that adults experience more severe memory decline issues, supporting our observation of elevated mental health challenge scores in participants over 18 years of age.

The study by Alhaj et al. [26] among UAE university students identified high rates of nomophobia and FOMO, consistent with our findings. Their study revealed significant correlations between these digital-related fears and mental health issues, including depression, anxiety, and stress.

Sulaiman et al. [19] found that active social media use, compared to passive consumption, tends to have a more negative impact on individuals' well-being. Their research demonstrated that frequency and duration of social media use can intensify negative mental health impacts across age groups and cultures, despite some potential benefits. They identified cyberbullying and other adverse online experiences as primary contributors to negative mental health outcomes.Group statistics for gender

Table 4. Group statistics for gender

	Gender	N	Mean	Std. Deviation	Std. Error Mean
Hours	Female	410	2.86	1.121	0.055
	Male	123	3.54	1.176	0.106
FOMO	Female	405	2.30	1.349	0.067
	Male	123	2.67	1.277	0.115
Crisis_Exposure	Female	408	2.59	1.470	0.073
	Male	122	3.07	1.427	0.129
Pressures_Parenting	Female	404	3.13	1.421	0.071
	Male	118	3.42	1.349	0.124
Inappropriate_Content	Female	406	2.52	1.371	0.068
	Male	121	3.36	1.303	0.118
Nomophobia	Female	407	2.40	1.346	0.067
	Male	122	2.67	1.387	0.126
TAD	Female	407	2.23	1.301	0.064
	Male	122	2.78	1.364	0.123
Hoarding	Female	408	2.88	1.401	0.069
	Male	121	3.17	1.362	0.124
Phubbing	Female	408	2.00	1.116	0.055
	Male	122	2.36	1.267	0.115

Table 5. One-Sample Proportions Confidence Intervals (Value = High)

Interval Type	Observed			Asymptotic Standard Error	Interval	
	Successes	Trials	Proportion		Lower	Upper
SM_Pressure	120	548	0.219	0.018	0.186	0.255
Cyberbullying	23	547	0.42	0.009	0.028	0.062
FOMO	193	544	0.355	0.021	0.316	0.396
ADHD	92	545	0.169	0.016	0.140	0.203
Social_Isolation	161	544	0.296	0.020	0.259	0.336
Memory_Decline	161	545	0.295	0.020	0.259	0.335
Crisis_Exposure	241	546	0.441	0.021	0.400	0.483
Pressures_Parenting	333	536	0.621	0.021	0.579	0.661
Inappropriate_Content	246	542	0.454	0.021	0.412	0.496
Nomophobia	200	544	0.368	0021	0.328	0.409
TAD	196	544	0.360	0.021	0.321	0.401
DM_Loss	159	545	0.292	0.019	0.255	0.331
Hoarding	287	544	0.528	0.021	0.486	0.569
Phubbing	135	546	0.247	0.018	0.213	0.285
Social_Intelligence	149	545	0.273	0.019	0.238	0.312

Table 6. Participant segments based on mental health challenges

Cluster	*N*	*SM_Pressure*	*FOMO*	*Social_Intelligence*	*Social_Isolation*	*Memory_Decline*	*Crisis_Exposure*	*Pressures_Parenting*	*Inappropriate_Content*	*Nomophobia*	*TAD*	*DM_Loss*	*Hoarding*	*Phubbing*	*Average*
MC1	141	1.65	2.25	2.00	1.74	2.12	3.56	4.19	3.49	2.23	2.06	1.71	3.17	1.93	2.46
MC2	115	3.19	3.57	2.15	3.54	3.18	4.07	3.65	3.93	3.93	3.90	3.70	3.74	2.98	3.50
MC3	193	1.41	1.53	2.77	1.68	1.59	1.63	2.61	1.76	1.41	1.40	1.56	2.10	1.56	1.77
MC4	99	1.86	2.86	2.54	2.45	2.33	1.92	2.42	2.06	3.13	2.83	2.45	3.37	2.27	2.49

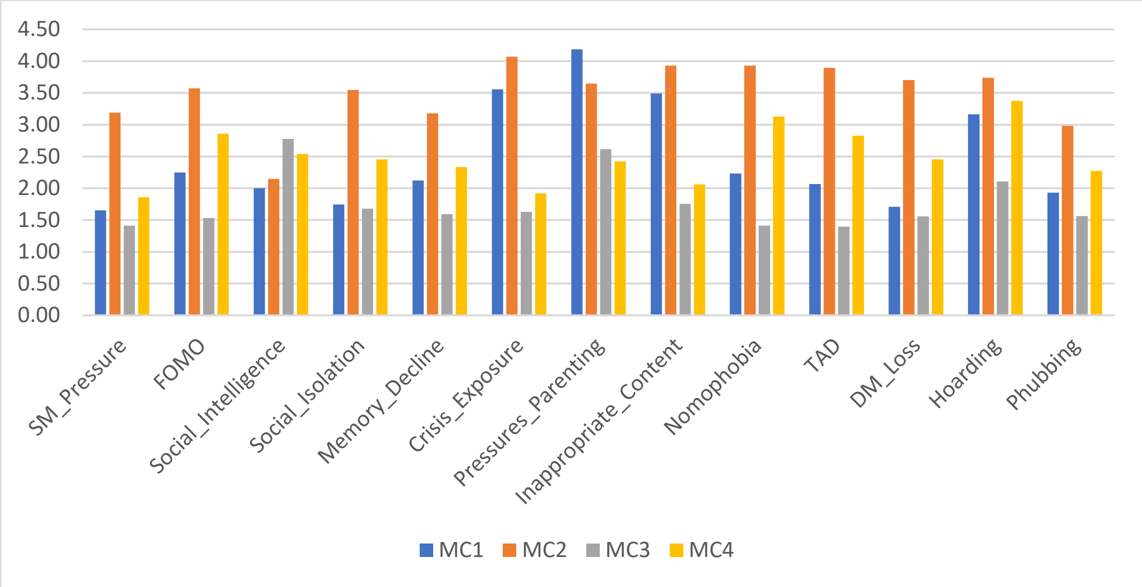

Figure. 4. Average values of variables for each cluster

Our finding of a strong correlation between TAD and FOMO aligns with multiple studies, including those conducted by Manzoor & Akhtar [28], Franchina et al. [29], and Li et al. [31] Additionally, our research revealed that 37% of participants experienced nomophobia, indicating widespread anxiety related to mobile device dependence. This prevalence rate is consistent with findings from Tomczyk and Lizde's study in Bosnia and Herzegovina [27].

The strong correlation we observed between nomophobia and TAD is corroborated by Çobanoğlu et al.'s research[33]. Similarly, our finding of a significant correlation between Nomophobia and decision-making loss aligns with studies by both Niazi et al. [35] and Yang et al. [34].

Moreover, Maia and Sousa's research among Portuguese young adults and adults demonstrated a significant positive correlation between Nomophobia and Phubbing [36], further validating our findings of a positive correlation between these mental health challenges.

Our study also resonates with Liu's work [41], which employed the K-means algorithm to predict mental health trends among college students. While Liu focused on academic populations, our decision tree analysis extends the application of predictive modeling to a broader demographic, identifying specific predictors of mental health challenges such as gender and age. Both studies affirm the utility of machine learning techniques in mental health research for developing targeted strategies.

Similar to the use of clustering in identifying mental health profiles in the Ontario study [42], our research applied cluster analysis to segment participants based on the severity of mental health challenges. Both studies highlighted that clustering methods can uncover nuanced population segments, with our study identifying a significant cluster (21%) experiencing severe mental health challenges. This underscores the value of data-driven methods for targeting interventions.

Like Vermeulen-Smit's study [44] , our study identified patterns of co-occurrence among digital mental health challenges, such as FOMO and TAD. Both studies highlight the clustering of risk factors, which can inform interventions aimed at mitigating cascading mental health issues. Furthermore, our findings on gender and age differences parallel the demographic insights in risk behavior studies, suggesting that tailored interventions are essential for addressing mental health disparities.

5. Conclusion

This study comprehensively reviews and analyzes mental health challenges in the digital era, identifying key issues, prevalence rates, and age and gender impacts. Through multidimensional analysis, significant relationships between mental health challenges are uncovered. Additionally, sample segmentation reveals distinct groups based on mental health challenge severity, providing insights for targeted interventions and prevention strategies.

The digital age presents both opportunities and challenges for youth mental health. This study investigated the key mental health challenges associated with technology use, addressing the research questions posed. In response to RQ1, we identified 15 primary mental health challenges, including social media pressure, FOMO, Nomophobia, and decision-making loss. RQ2 revealed that these challenges vary significantly across demographic groups, with older individuals and males facing higher levels of certain issues. RQ3 explored the distribution of these challenges in Iran, showing that a considerable proportion of the population suffers from severe mental health issues, with 21% of participants in Cluster MC2 experiencing high levels of mental health challenges. RQ4 examined the relationships between these challenges, with correlations highlighting the interdependencies between issues such as Nomophobia, TAD, and social isolation. Lastly, RQ5 identified distinct clusters of individuals based on the severity of their mental health challenges, emphasizing the need for targeted interventions.

While technology harbors great potential to enhance well-being, it is crucial to address its negative effects, particularly among younger generations who are more vulnerable to these challenges. The findings underscore the importance of adopting a multifaceted approach that includes education, awareness, moderation, and support systems to foster mental health resilience.

This study has several limitations. Firstly, the data was collected from a specific geographic region (Iran), which may limit the generalizability of the findings to other cultural or national contexts. Additionally, the study primarily relies on self-reported data, which can introduce bias due to social desirability or inaccurate self-assessment. The study also focused on participants' current experiences, without accounting for longitudinal changes in mental health challenges over time. Moreover, the exclusion of specific groups, such as those with diagnosed mental health conditions, limits the study's scope in understanding how pre-existing conditions interact with digital engagement.

Future research should aim to address these limitations by conducting longitudinal studies to track mental health challenges over time and across different cultures or regions. Expanding the sample to include more diverse populations would provide a broader understanding of how digital engagement affects mental health globally. Additionally, exploring the impact of emerging technologies, such as AI and virtual reality, on mental health will be crucial as these technologies become more integrated into daily life. Future work could also develop and evaluate AI-based tools and digital interventions that support mental well-being, offering personalized solutions for individuals at risk. Lastly, investigating the role of policy and educational initiatives, such as digital literacy programs, in mitigating the adverse effects of technology could lead to more comprehensive strategies for promoting mental health in the digital era.

By working collaboratively and implementing evidence-based solutions, society can create a balanced and mindful relationship with technology, ensuring that its benefits outweigh its drawbacks in the realm of mental health.

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