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Research Paper

Uncovering Emotions: Using IoT as a Psychodiagnostics Tool

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ABSTRACT

The current study is situated within the intersection of mood-tracking algorithms and draws on expertise in machine learning. Within the mixed-method approach, 40 participants were interviewed using semi-structured interviews and measured against a standardized mental health scale to gauge their moods. The work derives detailed understanding about the complex dynamics between users and these algorithms, describing their role in affecting emotional well-being amidst pervasive digital monitoring. It focuses more on the trends of screen time and how this relates to emotional states. This research strived to bring about not only the psychological implications of merging such algorithms in our digital lives, but also their efficacy in the clinical diagnosis of mental health disorders. This shows that increased screen time is strongly related to a rising susceptibility to major depression disorder and anxiety disorder. This baseline result showed important differences in the level of depression and anxiety among different content engagement groups and thus implies the differential effect of content types on the mental health of users. The study represents the potential of emotional tracking algorithms in detecting mental health problems, underlining the critical intersection of digital engagement and psychological well-being within the context of IoT.

Keywords: *IoT, Emotional tracking, Screen time, Emotional states, Digital monitoring, Algorithm, Social media, Instagram, YouTube*

Mental health disorders are a major public health concern, associated with serious social and economic burdens. On the part of the World Health Organization, depression was reported as one of the leading causes of years lived with disability worldwide, while an estimated 264 million people are affected. Further, it is estimated that anxiety disorders, very prevalent in nature, affect 284 million people worldwide. Bipolar disorder is less common but still affects an estimated 45 million people globally and is linked with significant morbidity plus mortality.

Traditional diagnosis of mental health disorders is usually done through clinical interviews and questionnaires based on self-reports. Subjective techniques are those that can be biased. More often than not, they do not enable continuous monitoring, and diagnosis is therefore often missed or delayed. IoT devices, due to their ability to collect data in perpetuity with respect to a number of physiological and behavior indicators, open up a bright avenue for diagnosis. Integration of IoT in mental health diagnostics can be helpful in early diagnosis

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and timely intervention. In general, interventions at an early stage are associated with better outcomes of treatment.

Inherent limitations of traditional diagnostic techniques have oriented growing interest in the use of artificial intelligence and machine learning to improve the accuracy and efficiency of mental health diagnostics. Artificial intelligence is the definition given to a computer system that can mimic human intelligence processes. These processes compose a big role of technologies that include natural language processing, predictive analytics, and deep learning. These technologies can really become a game-changer for mental health care by bringing more objectivity and fact-based insight into the condition of patients. (Esteva et al., 2019).

The research brings out the effectiveness of IoT in diagnosing mental health disorders, particularly through the analysis of emotional tracking algorithms currently used by social media platforms such as Instagram and YouTube. Basically, these are complex machine learning models that create and deliver content around the tastes and preferences of users, inferred from the interactions they make on these platforms in terms of likes, comments, and time spent on particular posts. The paper seeks to shed more light on the complicated dynamics that exist between users and these algorithms: how emotional states influence the interactions with content, and how effective these algorithms really are in tracking and responding to these emotions.

Advanced algorithms will make optimum use of user engagement across platforms such as Instagram and YouTube. By these algorithms, user interaction and preferences are followed to make sure that the personalized content is offered to the user. For instance, its algorithm considers several signals, like the posts a user likes, comments on, and even the time spent viewing specific content. According to Adam Mosseri, the head of Instagram, there are lots of algorithms, classifiers, and processes, all of which have an aim of their own to personalize the user's experience. By using technology, the platform aims at making full use of time for users through personalization of content in accordance with preference (Mosseri, 2023).

The recommendation system of YouTube is designed to keep people viewing, suggesting videos that may be in their best interests. It's very biased towards viewer engagement rather than just showing them the popular videos. In this way, it would most likely get users to watch the next video that would be suggested in a more personalized fashion catering to different viewer tastes (Glover, 2024).

Given the raft of data that is gathered by social media, there exists an immense possibility for using such data in mental health diagnostics. Indeed, algorithms for emotional tracking can be used to deduce user interaction and infer their emotional states. For example, changes in the kind and frequency of content a user is interacting with may suggest changes in mood or mental health status.

A study by Chancellor et al. (2016) highlighted that specific linguistic and behavioral patterns in social media posts could predict the severity of mental illnesses such as anorexia and bulimia. Similarly, De Choudhury et al. (2013) demonstrated that markers such as the frequency of depressive language and reduced social engagement on Twitter could accurately predict depression.

METHODOLOGY

Sample

This research adopts a mixed-methods approach, combining qualitative and quantitative data collection and analysis techniques. The sample consisted of 40 participants aged between 20 and 35 years, with a higher representation of individuals aged 24-27. The sample included 16 males and 24 females.

Procedure

Participants were recruited through online announcements via social media platforms. Data collection involved two primary methods: semi-structured interviews and standardized mental health scales. Participants were asked about their social media usage patterns, including the type of content they engaged with and their screen time. Following the interviews, participants completed the MHI (Mental Health Inventory) developed by (et.al, C. T. Veit) which comprises 18 items to assess their mental health status. The collected data were analyzed using statistical methods, using correlation and one-way ANOVA.

RESULTS

Table 1: The background information of the participants

Variables	**n(%)**	**n=40**
Sex		
Male	42	17
Female	58	23
Age		
20 – 23	37	15
24 – 27	51	20
28 – 31	2	1
32 – 35	7	3
Occupation		
Working	55	22
Non - working	45	18

The descriptive statistics of the mental health variables, specifically depression and anxiety, provide a comprehensive overview of the sample's emotional states. Table 2 presents detailed descriptive statistics for these variables

Table 2: ONE WAY ANOVA of Depression

Group	**N**	**Mean**	**Sd**
1	4	3.00	0.820
2	22	3.10	1.010
3	11	3.30	1.050
4	3	3.50	1.150
Total	40	3.22	1.090

The overall mean of 3.22 and standard deviation of 1.090 suggest that, across all groups, participants tend to experience moderate levels of depression with some variability. This comprehensive analysis of depression scores helps in understanding the emotional states of the participants, setting the stage for further exploration of how IoT and social media interactions can be leveraged for diagnosing and addressing mental health disorders.

Table 3: ONE WAY ANOVA of Anxiety

Group	N	Mean	Sd
1	4	2.70	0.920
2	22	2.30	0.960
3	11	2.55	1.010
4	3	2.60	1.050
Total	40	2.50	0.989

The overall mean of 2.50 and standard deviation of 0.989 suggest that, across all groups, participants tend to experience moderate levels of anxiety with some variability. This comprehensive analysis of anxiety scores helps in understanding the emotional states of the participants, setting the stage for further exploration of how IoT and social media interactions can be leveraged for diagnosing and addressing mental health disorders.

Table 4: One-Way ANOVA for Depression by Content Type

Source	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	12.341	6	2.057	3.114	0.015
Within Groups	23.659	33	0.717		
Total	36.000	39			

Table 5: One-Way ANOVA for Anxiety by Content Type

Source	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	10.264	6	1.711	2.768	0.028
Within Groups	20.736	33	0.628		
Total	31.000	39			

The ANOVA results indicate that there are significant differences in both depression ($F(6, 33) = 3.114$, $p = 0.015$) and anxiety ($F(6, 33) = 2.768$, $p = 0.028$) levels across different content engagement groups.

Pie chart 1: Classification of content

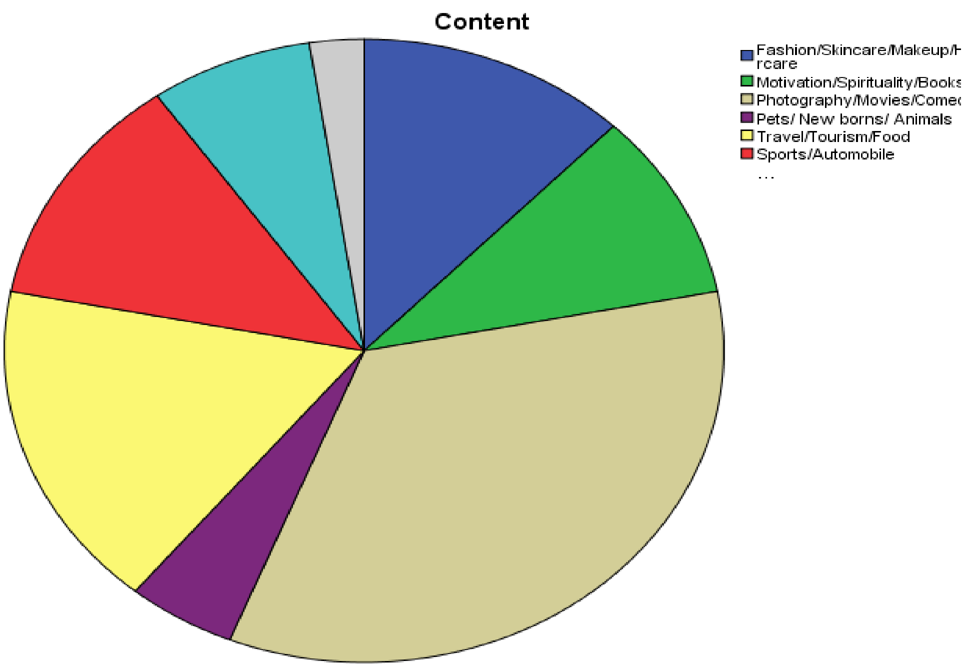

Table 6: Classification of content

Categories	Frequency	Percent
Fashion/Skincare/Makeup/Haircare	5	12.5
Motivation/Spirituality/Books	4	10.0
Photography/Movies/Comedy	14	35.0
Pets/ New borns/ Animals	2	5.0
Travel/Tourism/Food	7	17.5
Sports/Automobile	5	12.5
Healthy lifestye/Fitness	3	7.5
Total	40	100.0

The table provides a detailed breakdown of the types of content that participants in the study engage with on social media platforms, specifically Instagram and YouTube. The content categories are varied, covering a broad spectrum of interests. This diversity is critical in understanding how different types of content may correlate with the participants' emotional states and potential mental health conditions.

Table 7: Correlation b/w Screen Time and Depression/Anxiety

Variables	Screen Time	Depression	Anxiety
Screen Time	1	0.54**	0.45**
Depression	0.54**	1	0.62**
Anxiety	0.45**	0.62**	1

*Note: **p < 0.01*

The results show a significant positive correlation between screen time and both depression ($r = 0.54$, $p < 0.01$) and anxiety ($r = 0.45$, $p < 0.01$). Additionally, there is a significant positive correlation between depression and anxiety ($r = 0.62$, $p < 0.01$).

DISCUSSION

The possibility of revealing the potential of IoT technologies in mental health diagnostics, based on studies of emotional responses of social media users, is supposed to be done by revealing the emotional responses when interacting with materials on Instagram and YouTube. As the statistics and study results show, participants demonstrate moderate levels of depression and anxiety, which are in line with the studies and the high level of prevalence these days in people who frequently visit social networks. A mean depression score of 3.22 indicates that these participants are having problems at a moderate level. The kinds of content participants interacted with on Instagram and YouTube were also studied with their related emotional responses.

It was seen that people who consumed pet and animal-related content were more prone to depression, while those who used fashion, motivation, and lifestyle content had higher self-esteem. For example, watching videos of pets may be a source of comfort in the short term but it can also make one realize feelings of loneliness or longing that might lead to higher levels of depression. On the other hand, content that is self-improvement driven, such as fashion and motivation, could act to heighten one's self-esteem and, in turn, result in less depression.

These findings have numerous implications. First, they shed light on how IoT technologies can aid in extracting useful information about the mental health of users through their interactions on social media if integrated with these platforms. This opens up a very meaningful avenue for the development of predictive models and the creation of early warning systems in terms of mental health. For example, tracing changes in content consumption patterns, IoT systems could identify precarious emotional states and alert the user or involved mental health professionals for early interventions.

The findings of this study raise useful insights into the potential of IoT-based diagnosis of mental health disorders by using activities from social media. Because of the strong relation that exists between both the time of screen usage and mental health, appropriate, responsible usage of social media is important. These findings may form the basis of an answerable IoT-based system that would enable real-time monitoring and early intervention to promote better mental health outcomes. Further research in this area of interest is in the future. Hopefully, future research will also help address problems and limitations of the research areas and extend the scope to other population categories and social media platforms.

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Conflict of Interest

The author(s) declared no conflict of interest.

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