Using Passive Sensing to Identify Depression

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Abstract. Depression is a common mental health issue that affects people's thoughts, behaviours, and feelings. However, depression can often be under-diagnosed or under-treated. Early identification of depression can help to reduce the severity of the condition. Passive sensing, which captures data through mobile applications and wearable devices, has been shown effective in monitoring and identifying mental health problems, including depression. In line with the scope of AISoLA for Digital Humanities to explore the challenges and opportunities of interdisciplinary action to develop better practices in research, this paper explores the efficacy of passive sensing through mobile applications and fitness trackers to identify signs of depression among 52 adults in a three-week study. Sensing data captures calls, text messages, locations, nearby devices, usage of social applications, physical activity, sleep duration and quality through the AWARE and FitBit applications. The paper also investigates differences in the behaviour between people without depression and people with symptoms of depression, and it explores which sensor data can help to accurately identify depression. The results show high accuracy of certain sensing data to identify symptoms of depression. Depression is associated with reduced physical activity, higher sleep efficiency, increased number of incoming calls, increased number of visited places and reduced application use. Differences between behaviours show that people with symptoms of depression are less active, have a higher sleep score and receive more calls compared to people without symptoms. These findings should be interpreted within the methodological issues that are discussed in this paper in relation to wider research in sensing technology that aims to identify and monitor depression, including small sample sizes and lack of information about participants.

Keywords: Passive sensing, smartphones, fitness trackers, depression

1 Introduction

1.1 Symptoms of depression

Depression is a common mental health condition that affects people's thoughts, feelings and behaviour [1]. It is estimated that approximately 280 million people across the world have depression [2]. Common symptoms of depression include sleep and appetite disturbance, and lack of interest or pleasure [3]. Depression is often not diagnosed in a timely manner [4], but early detection and intervention of depression can help to avoid many negative impacts of depression [5].

According to the Diagnostic and Statistical Manual of Mental Disorders [DSM5], depression is associated with lower physical activity, and mood and sleep disturbance. A study by Kaneita et al. [6] showed that people who sleep less than 6 hours or 8 or more hours per day are more likely to be depressed compared to people who sleep between 6 and 8 hours. This study also showed that sleep sufficiency was decreased in people with more symptoms of depression. Changes in physical activity are another behaviour that is associated with depression. A review of the long-term effects of depression on physical activity [7] showed that depression was associated with reduced physical exercise. Social disconnectedness and perceived isolation are also predictors of depression and have a bi-directional relationship with their influences [8]. Passive sensing has been shown to be a promising approach to identifying mental health problems, including depression [9-11]. This paper focuses on the identification of symptoms of depression through passive sensing.

1.2 Passive sensing to identify depression

A common way to passively capture data to identify mental health issues is through mobile phone applications and wearable devices, such as fitness trackers. This approach requires minimum effort from participants. Some of the behaviours that are associated with depression, such as sleep disturbance, can be captured through the sleep assessment algorithm integrated into the smartphone applications of wearable devices such as fitness trackers or smart watches. An indicative example is the study by Narziev et al. study [9], who used smartphone and smartwatch applications to identify depression in 20 participants through behaviours associated with depression, including physical activity, sleep levels, mood and food intake. The results from this study showed that behavioural data from passive sensing through smartphones and wearable devices was correlated with participants' activity, sleep and mood as they were assessed through self-reported data. Another study by Wang et al. [10] used the StudentLife dataset to explore whether a smartphone application can identify different outcomes for 48 university students. The authors found correlations between depression and sensing data, especially for sleep, communication and location data, meaning the number of places that people visited during the ten-week study. A two-week study with data from

28 people showed a relationship between symptoms of depression, phone use and visited locations [11].

Accelerometers and global positioning systems sensors are some of the most widely used smartphone sensors in passive sensing for health and well-being; however, a systematic review by Trifan et al. [12] highlighted a possible gap between smartphone outcomes and clinical knowledge in this field, and the need for higher user engagement and further validation of the technology that is under investigation, including larger sample sizes. These methodological issues in research may explain varying results in studies. For example, in contrast to the study by Wang et al. [10], other research evidence suggests that mobility that is measured through GPS location tracking is not associated with depression [13]. Issues arise from converting raw data into summaries, known as features, especially when using existing technology in research studies that provide only featured data instead of raw data. The frequency with which data is collected and sparsity because of missing data are also possible explanations for different research findings [13]. Despite those issues, passive sensing through smartphone applications and wearable devices has the potential to improve the monitoring and management of mental health conditions [14].

The present paper analyses data from our study at University College Cork to explore the accuracy of passive sensing. We collected behavioural data for people’s physical activity, sleep, and communication patterns, to identify depression. Another aim of the paper is to assess which behavioural features can accurately identify depression. The paper also investigates behavioural differences between people who experience symptoms of depression with people without depression, such as differences in sleep quality. While most of the past research recruited young university students as participants, this paper uses participants from a broader age group and collects data using numerous sensors that have been shown to effectively identify symptoms of depression. Section 2 in this paper introduces the methodology of our study. Section 3 presents the results and Section 4 discusses the findings in light of past research while considering limitations and opportunities for further research in line with the scope of AISoLA to contribute to better research practices.

2 Methods

2.1 Data collection

We collected data for three weeks using the AWARE smartphone app [15] and a FitBit fitness tracker and associated smartphone app (Table 1). Both applications have been used in research on passive sensing for monitoring different social and health issues [16]. The authors used both applications in order to collect both physical sensor data and communication and social connection data from participants. Data from both applications were collected for three weeks to allow sufficient time to collect enough data. Past research collected data between two to several weeks. In a study by Saeb et al. [11], the researchers collected data from 40 participants for two weeks, 28 of which provided enough data from sensors for analysis. The three-week duration of the present study was decided because of this possible lack of sufficient data and to avoid issues with recruiting enough participants for a longer study.

Data for participants' calls, text messages, changes in location, nearby Bluetooth devices and use of social applications was collected through AWARE. A FitBit Inspire 2 fitness tracker was used to collect data on participants' physical activity and sleep. Participants were asked to keep their Bluetooth and Wi-Fi activated for the duration of the study. Data was automatically collected without effort from participants. We installed the two applications on participants' smartphones, and they were asked to wear the fitness tracker for three weeks. Participants were provided with instructions and a user guide showing them how to charge their fitness tracker.

2.2 Participants

Data was collected from 52 adults, 18 years old or older using a random and non-clinical sampling strategy. Table 1 shows the minimum and maximum values of sensor data. Participants' demographic information is presented in Table 2. Data on participants' demographic characteristics was also collected, including their age, gender, employment, level of education, and marital status. At the beginning of the study, we asked participants to complete the short version of the Geriatric Depression Scale (GDS) [17] to assess feelings of depression. The short form of GDS includes 15 questions about people's moods, activities, and feelings to be answered with Yes/No responses. GDS scores vary from 0 to 4, indicating no depression symptoms; 5-8, indicating mild symptoms of depression; 9-11, indicating moderate depression; and 12-15, indicating severe depression. For the purposes of this study, we grouped people with GDS scores from 0 to 4 in a group of people without depression, and people with GDS scores from 5 to 15 in a group of people who experience depression symptoms. This categorization was decided because we are interested in identifying depression at an early/mild stage. This study gained ethical approval from the Social Research Ethics Committee of University College Cork (number 2021-249) and complied with the General Data Protection Regulation.

Table 1. Sensor data from AWARE app and FitBit tracker

		Depression symptoms	No symptoms
Application	Sensor data	Min-Max values in a day	Min-Max values in a day
AWARE	Incoming calls (number)	0-9	0-7
	Incoming calls (duration)	0-4910 secs	0-6002 secs
	Outgoing calls (number)	0-19	0-21
	Outgoing calls (duration)	0-6425 secs	0-6358 secs

	Received texts	0-19	0-53
	Sent texts	0-9	0-9
	Locations (number of changes in location)	0-318	0-508
	Bluetooth (detecting nearby devices)	0-4502	0-4180
	Application usage	0-343	0-300
FitBit	Physical activity (duration)	0-793 mins	0-931 mins
	Sleep duration	119-750 mins	46-714 mins
	Sleep quality score	82-100	15-100

2.3 Data processing and analysis

For sensor data from the AWARE application, the total performance of each behavioural feature was calculated for the three-week study duration. We calculated the sum of incoming and outgoing calls and their duration in seconds, the sum of received and sent text messages, and the number of Bluetooth devices that were detected near each participant to provide a measure of how many other people our participants encountered during the day. The number of changes in location was calculated using the longitude and latitude of each location. Changes in locations were identified if the distance between them was at least 400 meters and people spent at least 300 seconds in each location to avoid traffic delays being recorded as transitions [18, 19].

Application usage was measured based on the number of times that participants used a social networking application, including Whatsapp, Skype, Messenger, Instagram, Viber, MS Teams and Zoom. For data from the FitBit application, we calculated the duration of physical activity and the sleep duration across the three weeks of the study. The sleep efficiency score was generated by the FitBit app based on participants' heart rate and movement during sleep utilising the Fitbit sleep score algorithm. Missing values were replaced with the mean of each behavioural feature for both groups of people with and without symptoms of depression.

A logistic regression was used to assess the accuracy of the overall sensing data to identify depression as a binary outcome and to show the correctness of the results in the model. Behaviour differences between the group of people without depression and the group of people who experience symptoms of depression were assessed using independent samples t-tests that assess mean differences between two independent groups. Finally, binomial regression models were used to explore which of the behavioural features could accurately identify depression. Such models predict the odds of a variable falling into one of the two categories of the outcome (symptoms of depression or no symptoms). Confidence intervals (CI) show the range of possible values for each variable.

Table 2. Demographic characteristics for participants per group

Application	People with symptoms of depression	People with no symptoms	P-value
N	12	40	
Age [mean, SD]	51 (24)	47 (19)	0.073[1]
Gender [number]			0.538[2]
Males	4	16	
Females	8	24	
Employment [number]			0.138[2]
Retired	6	13	
Undergraduate student	2	3	
Postgraduate student	0	2	
Full-time employed	2	16	
Part-time employed	0	5	
Unemployed	2	1	
Education [number]			0.307[2]
Secondary	3	5	
Undergraduate	5	12	
Postgraduate	4	23	
Marital status [number]			0.056[2]
Married	1	13	
Single	6	23	
Divorced/separated	3	2	
Widowed	2	2	

[1]Indepedent samples t-test
[2]Chi-square test

3 Results

Initial analysis with raw data showed that reduced activity could identify symptoms of depression (p= 0.043) (model 1 in Table 3). In model 2, missing values were imputed with the mean score in each sensor. Because of the small number of people with symptoms of depression in this study (N= 12), we used the Synthetic Minority Oversampling Method (SMOTE) [20]. The logistic regression model achieved 82.8% overall, with 78.1% accuracy in identifying no symptoms, and 87.5% accuracy in identifying symptoms of depression. Binomial regression models showed that reduced time of physical activity (p= 0.002) and reduced application use (p= 0.032) could identify the presence of symptoms of depression (Table 3.). Higher sleep efficiency score (p = 0.046), visiting more locations (p= 0.005) and increased number of incoming calls (p= 0.002) could also identify depression.

Table 3. Individual sensors for identifying depression

Sensors	Model 1			Model 2		
	Odds ratio	CI	Sig.	Odds ratio	CI	Sig.
Activity duration	0.99	0.99-1.00	**0.043**	0.99	0.99-1.00	**0.002**
Sleep duration	1.00	1.00-1.01	0.462	1.00	1.00-1.00	0.487
Sleep score	1.02	0.96-1.10	0.521	1.10	1.00-1.20	**0.046**
Application usage	1.00	1.00-1.00	0.935	0.99	0.99-1.00	**0.032**
Received texts	1.00	0.96-1.04	1.000	0.95	0.90-1.01	0.072
Sent texts	0.98	0.91-1.04	0.447	1.02	0.95-1.10	0.523
Number of outgoing calls	0.98	0.94-1.02	0.282	1.00	0.96-1.04	0.880
Outgoing calls (duration)	1.00	1.00-1.00	0.541	1.00	1.00-1.00	0.337
Number of incoming calls	1.05	0.97-1.12	0.227	1.17	0.95-1.17	**0.002**
Incoming calls (duration)	1.00	1.00-1.00	0.467	1.00	1.00-1.00	0.149
Changes in location	1.01	0.99-1.03	0.176	1.04	1.01-1.06	**0.005**
Bluetooth	1.00	1.00-1.00	0.286	1.00	1.00-1.00	0.057

Model 1: results with raw data, Model 2: results after applying SMOTE and missing values calculations

Independent samples t-tests showed that people who experienced symptoms of depression had significantly more incoming calls [t(62) = -1.73, p = 0.045], more changes in location [t(62) = -2.58, p = 0.006], and lower duration of physical activity [t(62) = 3.00, p = 0.002]. Figures 1 and 2 present the sensor data of people with symptoms of depression and the control group without symptoms in percentages using the highest score in each sensor as 100%. No significant difference was found between the two groups in the duration of sleep [t(62) = -0.61, p = 0.274], the sleep efficacy score [t(62) = -1.00, p = 0.161], their application usage [t(62) = 1.61, p = 0.057], the number of received and sent texts [t(62) = -1.11, p = 0.135, t(62) = -0.09, p = 0.466, respectively], the number and duration of outgoing calls [t(62) = 0.36, p = 0.360, t(62) = 1.16, p = 0.125, respectively], the duration of incoming calls [t(62) = 0.48, p = 0.316], and in the number of Bluetooth contacts that were detected near them [t(62) = 1.38, p = 0.086].

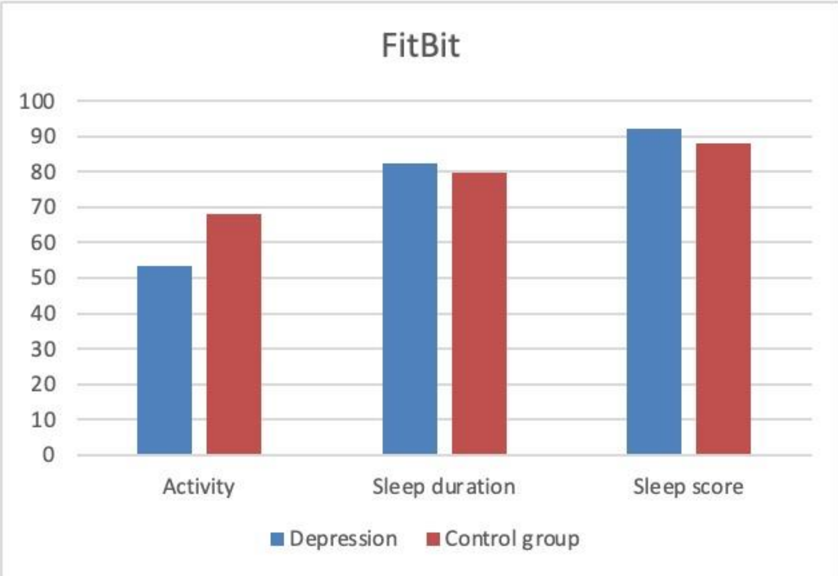

Fig. 1. Differences in behaviours between people with and without depression in activity and sleep.

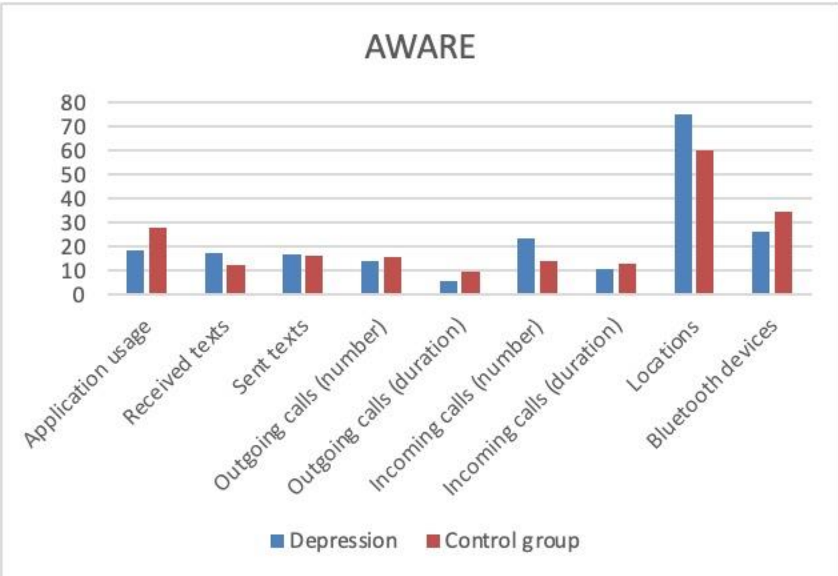

Fig. 2. Differences in behaviours between people with and without depression in communication, changes in location and detected Bluetooth devices nearby people.

4 Discussion

This study explored the accuracy of passive sensing to identify symptoms of depression. Moreover, the study investigated which sensors from mobile applications and fitness trackers are accurate in identifying depression and whether there are behavioural differences between people with symptoms of depression and people without symptoms. The results from this study confirmed past findings about the accuracy of passive sensing to identify symptoms of depression. Depression was associated with reduced physical activity, higher sleep efficiency, an increased number of incoming calls and locations, and reduced use of social applications.

The results of reduced physical activity are in line with past research [7]. Incoming calls can accurately identify symptoms of depression [21]. Past research showed that reactive phone users answer more phone calls than make calls themselves and are more likely to experience symptoms of depression [22]. Our finding that people with depression visit more places is in contrast to existing evidence [10,11]. This increased number of visited places could reflect the need of people with symptoms of depression to meet people. Our finding that people with symptoms of depression used fewer social applications is consistent with past research and can be explained by social withdrawal, which is often observed in depression [23]. Our results about improved quality of sleep in people with symptoms of depression are not in line with past research [6]. However, FitBit calculates the sleep score based on the duration of sleep, the time spent in different sleep stages and how relaxed people are during sleep. People with depression often present different sleeping patterns varying from oversleeping to sleep deprivation. Our behavioural results did not show a difference in the sleep duration between people with depression symptoms and those without symptoms. This may be because of the different sleep disturbance issues across different people with depression, and this result may affect their efficiency score.

This study showed that other types of communication, including outgoing calls and text messages, could not identify depression or its absence and thus did not confirm past research that showed reduced social activity and communication [8] in people with depression symptoms. This failure of our sensing data to reproduce past results may be because of the small sample size, especially in the group of people with symptoms of depression. This is a limitation of the study compared to some past studies. A systematic review of methods for passive monitoring of depression [24] has shown past studies' pitfalls in this field, including the lack of necessary information, such as information about participants' recruitment strategies, and information about participants and the features. Other issues that were observed in this review about studies using passive sensing to identify depression include their small sample sizes and short follow-up duration [14, 24]. This study was part of a larger project on ageing that recruited people between 18 and 50 years old, and people 65 years old or older. Thus, data from people between 51 and 64 years old was not collected. Another limitation of our study is the inability to group people with depression symptoms in more groups depending on the severity of symptoms because of the small number of people with symptoms and the imbalanced gender ratio with female participants being more than male participants. Similar to past studies, the issue with accuracy and amount of data that is often missing affects data analysis. For example, Table 1 shows 0 as the minimum value of changes in location. This value is inaccurate because participants visited University College Cork at the beginning and the end of the study. Improvements in technology for monitoring mental health and wellbeing should be taken into account in future research. In addition, future research with larger sample size could employ more personalized machine learning models to identify symptoms of depression of the severity of the symptoms, for example by identifying subgroups within the sample with similar behavioural patterns. Group-based prediction models have been found to be more accurate in identifying other outcomes compared to generalized models [25].

5 Conclusions

Concluding, this study extends past research to explore the identification of symptoms of depression through passive sensing by including people from a broader age range and by combining data from both smartphones and fitness trackers. The results showed the accuracy of certain sensors for activity, sleep, calls, application use, and changes in location to identify symptoms of depression; however, this finding should be interpreted in relation to the methodological issues that have been identified in this field, including the sample size and the information that is provided from each study to enable comparisons. Future research could address those limitations to improve the generalizability of results and the reproducibility of research, for example, through group-based or personalized predictions models. The challenges in this field that are discussed in Section 4 could be considered by researchers who can contribute to the development of interdisciplinary teams to design technological solutions based on the needs of users. Research in this field of technology, mental health, and wellbeing can result in more accurate tools to assess ourselves in our everyday life and prevent the development or more serious symptoms that require professional help.

The results and evaluation of the present study contribute towards adopting more effective research practices. Similar to the Digital Humanities track of AISoLA, the authors of this paper form an interdisciplinary team with backgrounds in computer science, psychology and social work who explore the challenges and opportunities of technology to support people in their everyday life through different research studies.

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