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The Application of Machine learning (ML) approaches in Digital Health Interventions

R.Gopinathan[1], Priti Gupta[2], Ayan Das Gupta[3,*], Muthukumar Subramanian[4], DSK Chakravarthy[5]
[1]Associate Professor, Department of Mechatronics Engineering, Sri Krishna College of Engineering and Technology, Coimbatore.
[2]Department of Economics, Ramesh JhaMahila College, Saharsa, Bihar, India
[3]WBES, Assistant Professor, Postgraduate Department of Geography, Chandernagore Government College, Hooghly, West Bengal, Chandernagore Government College affiliated to the University of Burdwan.
[4]CoE & Professor, Sri Siddhartha Academy of Higher Education (UGC Approved Deemed to be University), Tumkuru, Karnataka, India.
[5]Agile Coach, Virtusa Consulting Services Private Limited
***Email :** dasguptaayan11111@gmail.com

ABSTRACT
Digital Health Intervention or DHI has shown promising benefits in healthcare sectors due to its low-cost and quick approaches. Apart from this, patients became able to interact with the clinicians remotely and schedule treatments which benefited the patients as well as the clinicians. Clinicians, in this context, used Machine Learning (ML) architectures to diagnose and predict diseases by collecting relevant information from patients. The entire process can be carried out digitally by DHI after building trust and liability between clinician and patient. This study has tried to find how ML and DHI affect the satisfaction levels of patients and clinicians. To accomplish the outputs, correlation, regression and descriptive analysis have been carried out in IBM SPSS by considering some independent and dependent variables. Dependent variables selected are accuracy in anxiety, depression and sadness prediction by ML in DHI; unplanned hospital visits without any schedule; patient's satisfaction and clinician's satisfaction. The Independent variable selected is months of ML use in DHI which has shown a significant impact on the dependent variables.
Findings suggested that clinicians are satisfied with the ML and DHI as the treatment and patient visits have been scheduled. ML is accurate enough to predict psychological illness; however, further improvement is necessary. Patients' satisfaction levels fluctuated because they did not receive promising interaction from the clinicians, every time.
Keywords: *Internet o Things, Machine Learning, Digital Healthcare, telemedicine, clinicians*

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INTRODUCTION

Digital Health Intervention or DHI is defined as providing tele-support, telemedicine, medical strategies, monitoring and caring for patients to reduce the cost of personal meetings. As everyone knows, personal meetings require transportation of the patients as well as doctors which lead to a reduction of savings. Therefore, when DHI has been implemented in various healthcare sectors, it showed a significant promise in the improvement of patient health [1]. Conventionally, phone calls, google meet, WeChat video calling services have been used for iterating with the patients. However, data privacy and security is major concern in the digital platform [2]. Apart from this, online meetings require the presence of the clinicians at that time which may not be possible for every respective clinician. Thus, researchers have found a more promising technique; the Machine Learning (ML) approach which will provide "*computerised decision support*". As of now, many healthcare sectors have integrated the ML approaches including cancer, cardiology, psychology, dermatology, diabetes and many more [3]. The ML accurately detects, diagnoses, prognoses and differentiates the patient data which help in the development of decision support.

ML requires training with large datasets containing labelled numerical, string and pictorial data. After that, the ML can detect and diagnose patient data to identify whether a person has diabetes or not. The data generally include the behavioural, clinical, genetic and other data which are relevant for the prediction of disease [4]. Patient data can be obtained through a digital platform and the diagnosis can be done easily without any face-to-face interaction. As security is a concern, blockchain and other encrypted technologies are being used which have shown a promising outcome. Therefore, DHI using ML helped

both the clinician and patients to receive real-time and quick care by sitting at home. Apart from this, ML together with other Internet of Things (IoT) technologies helped the clinicians to schedule treatment and patient care which resulted in a better treatment [5]. ML has taken the place of accurate DHI; however, some remarkable limitations did not allow every healthcare sector to integrate this technology.
This research paper is going to analyse the application of ML in DHI through SPSS analysis. The paper organisation includes, past literature to uphold the previous studies on the digital intervention using IoT and ML; a research methodology to describe the detailed methods used; analysis and interpretation of the outputs; discussion of the outputs; and finally, the entire study has been concluded.

LITERATURE REVIEW

Various applications are available on the play store and app store which can be considered helpful; however, the app developers add various discrete tools and features which are not highly useful. The clinicians reported that those features facilitate a few meaningful information and suggestions; however, for the effective justification of a patient medical record, those mobile applications cannot be used [6]. Those applications contain impressive and innovative features; however, lack the practical properties that can be given to a particular patient. Thus, researchers are focusing on ML, Artificial Intelligence and IoT for the betterment of digital patient care. As the clinicians reported, those applications are not addressing the *therapeutic relationships* and only focus on patients or clinicians; thus, the applications require development [7]. The author suggested that, instead of creating new applications, the developers need to focus on the reframing of those apps. After that, those applications will be able to maintain a strong therapeutic relationship between patients and clinicians, rather than working around them [8].
When DHI and therapeutic relationships are matters of choice, liability, transparency and trust are the major concerns. Before delivering therapeutic care, the clinicians and patients need to develop trust between each other. A possible solution for this is to organise a face-to-face meeting before practising DHI [9]. Apart from this, a responsible healthcare professional is required who will provide promising care over the digital meeting as well. The conventional applications are still used by many patients and clinicians; however, an emergency number (safety net) is provided to the patients and clinicians to develop legal liability.
Clinicians, patients and other researchers are recommending face-to-face meetings before making them digital. After that, using digital applications, clinicians can monitor the patient data and patients can monitor the medications. When responses between doctor and patient are interrupted, the patient or doctor can schedule a video meeting or personal visit via the application. Other interventions can be easily provided using the digital platform; such as diet charts, exercising monitoring, some psychotherapy and many more [10].
The usage of machine learning has also taken place in healthcare departments. Before the time of technical development, many medical tests have been examined with difficulties. However, after the applications of ***ML*** or machine learning the development of medical evaluation has evolved. All of the hardware-related tools and the components of medical assessments can be addressed as the components of machine learning. For example, the process of *MRI* scan is one of the most important and effective contributions of machine learning in healthcare management [11].
On the above-attached image, it can be seen that the scanning process of *MRI* has been managed with the machine. The above-attached figure has demonstrated an automated *MRI* machine that can measure the needed measurements of a human body through *Magnetic Resonance Imaging*. The scanning process is maintained with the AI feature of the machine.

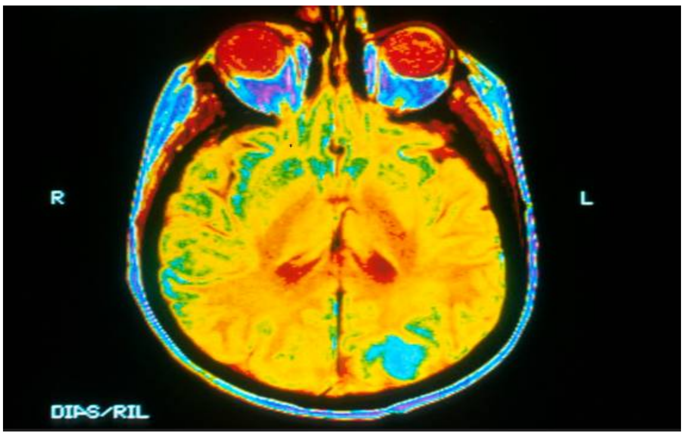

Figure 1: MRI Scanned image of the brain[12]

The above image has demonstrated the scanned imagery which has been done with an ***MRI*** machine. On the other hand, a few other components of medical machine learning healthcare are used to determine the kind of disease that the patient is suffering from [12].After the application of machine learning such a wide aspect of treatment has been managed. The classification process to identify the health issue can be managed with the help of AI tools which is also addressed with *ML*. Machine learning readings can serve urgent medical information related to the issues that have been detected within the patient. On the other hand, during such critical patient's assessment machine intelligence helps doctors to address the patients as soon as possible with the help of machine learning. It is not that only huge machines and their usages are known as machine learning in healthcare, the AI evaluation process has the ability to match similar medical cases to find solutions instantly. The process of *CAT* scanning or *computerized axial tomography* is also accessed with machine learning. Over the years of past medical treatment that has been treated with *CAT* has helped patients to take the necessary steps against the issues soon as possible. In the segment of *ML* in healthcare, the process of *CAT* has maintained such immense responsibility for the patients [13].

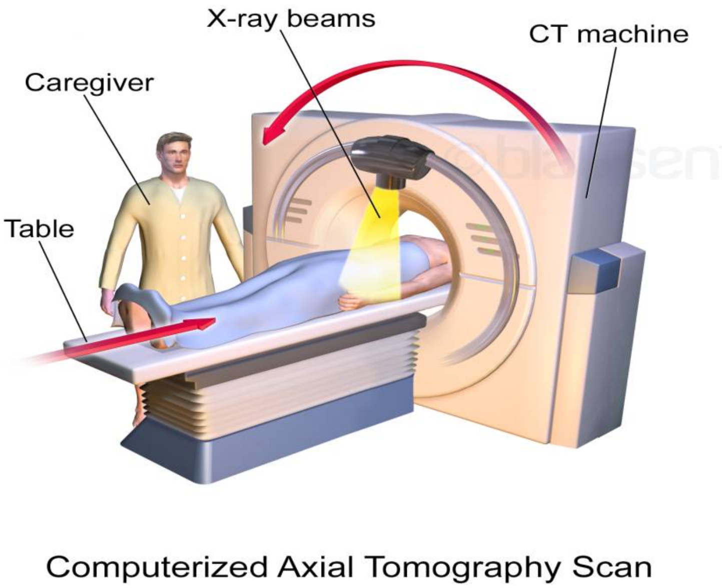

Figure 2: Computerized axial tomography[13]

The attached figure has demonstrated the usages of Computerized axial tomography in the healthcare department. The process of CAT is a non-pain treatment that is used to detect proposed health issues for finalization.

Multiple components of Machine learning are present in the healthcare department that can be used to treat multiple health issues within a very short period of time. The most helpful accessibility of ML is predicting intelligence which helps patients to take precautions and get assured with the health issue. It has been seen that the help of proper machine learning in the medical aspect has changed the very structure of treatments for the patients. Each and every component or tool of ML has helped with digital health interventions [14].The literature has found the common ML approaches which are used in healthcare systems and the DHI practices which benefitted the clinicians and patients. Based on the past literature, the research has identified the impact of ML and DHI on several dependent variables.

RESEARCH METHODOLOGY

The currency research has selected primary research on clinicians and patients to understand whether the ML approaches truly benefited them in terms of DHI. A total of 150 patients and 150 clinicians have been selected to answer questions related to the digital medical intervention. The questions were collected through an online survey and then converted to numerical form for identification of statistical significance. The selected 300 participants have used the ML approaches (mobile apps, digital care and so on) to build DHI. The majority of them responded that they have come to a face-to-face meeting before shifting to digital practice. However, the data have been collected related to identification of sadness, depression, anxiety, satisfaction on the DHI, recognition accuracy, reduction in unplanned hospital visits and treatment scheduling accuracy. Responses on these data have been collected on an excel dataset and then analysed using IBM SPSS version 26.

More specifically, correlation analysis and descriptive statistics have been carried out to understand how the Machine Learning approach of DHI benefits them in terms of those factors. Therefore, the *months of ML use for DHI* has been considered the independent variable and the following factors have been considered dependent variables.

Dependent variables: Accuracy in sadness identification; Accuracy in anxiety identification; Accuracy in depression prediction; patient's satisfaction on DHI; Clinician's satisfaction on DHI; and an unplanned hospital visit.

Patients and clinicians have provided answers on close-ended options that include accuracy identification. To simplify, the clinicians have been asked to provide anxiety and depression prediction accuracy of ML in DHI. They were also asked to mention their duration of ML use in DHI. They mentioned the duration of ML use (in months) and the respective prediction accuracies. After that, the numerical values were kept in Microsoft Excel for further analysis. On the other hand, patients have been asked to provide their satisfaction level using DHI on a Likert scale from 1 to 7 where '1' defines highly dissatisfied and '7' defines highly satisfied. Clinicians responded to the assumed percentage of patients' unplanned hospital visits which have been recorded in Excel to identify whether using DHI and ML has reduced the unplanned hospital visits or not. After the data have been converted to numerals, correlation analysis has been carried out along with descriptive statistics. Pearson correlation and two-tailed significance values have been considered to understand how ML and DHI affect conventional healthcare procedures.

A Pearson Correlation value close to +/-1 represents the two strongly correlated variables. A significance or p-value less than 0.05 ($p<0.05$) represents a statistical significance. Apart from correlation analysis, descriptive statistics have been identified to understand the minimum and maximum values which define the minimum and maximum accuracy respectively. Lastly, Accuracy in sadness, anxiety and depression prediction, and unplanned hospital visits have been considered independent variables to understand the impact on clinicians' satisfaction (dependent variable) by regression analysis. After the primary analysis, secondary available journal articles (2018-2022) have been analysed to validate the current study.

Research Questions

How does Machine Learning in DHI affect the accuracy of anxiety, depression and sadness prediction?

How does ML in DHI affect the satisfaction level of clinicians and patients?

How does ML in DHI affect the treatment schedules and unplanned hospital visits?

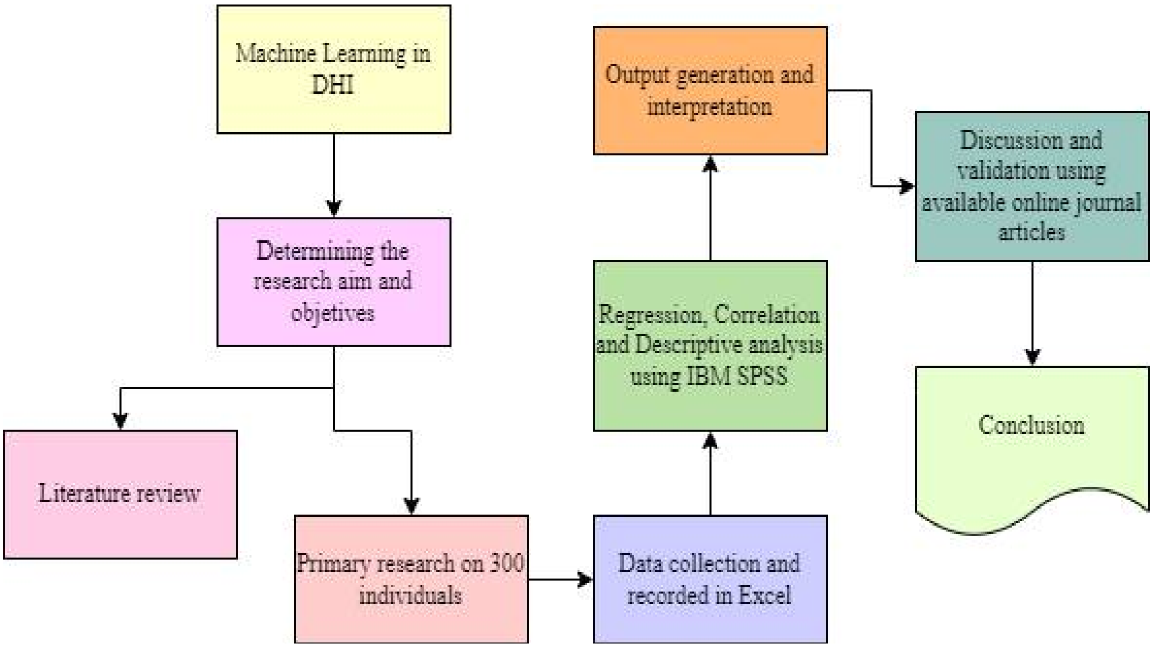

Figure 3: Research Flowchart

ANALYSIS AND INTERPRETATION

The methodology section has already mentioned, a total of 3 analyses have been carried out: Pearson bivariate correlation, descriptive statistics and regression analysis. The output tabular data are shown below

TABLE I. CORRELATION ANALYSIS OUTPUT

Correlations								
		Months of ML use for DHI	**Sadness identification accuracy (%)**	**Anxiety identification accuracy (%)**	**Depression prediction accuracy (%)**	**patient's satisfaction on DHI**	**Clinician's satisfaction on DHI**	**Unplanned hospital visit (%)**
Months of ML use for DHI	Pearson Correlation	1	.927**	.902**	.868**	.288	.869**	-.835**
	Sig. (2-tailed)		.001	.000	.002	.219	.001	.000
	N	20	20	20	20	20	20	20

**. Correlation is significant at the 0.01 level (2-tailed).

Table I shows the correlation output of the entire mode from where months of ML use in Digital intervention has been considered to affect the dependent variables. DHI and ML have positively impacted the accuracy in sadness ($p<0.002$; 0.927), anxiety ($p<0.001$; 0.902) and depression prediction ($p<0.003$; 0.868). Moreover, the Pearson correlation values greater than 0.8 suggest that ML and DHI improved the accuracy in prediction (responses of clinicians) (Figure 4). Patient's satisfaction has been determined by the months of DHI practice which showed no statistical significance ($p>0.2$). It suggests that a patient's satisfaction level is highly variable and not related to the duration of DHI practice. On the other hand, the clinician's satisfaction level is statistically significant with the DHI ($p<0.002$; 0.869). However, satisfaction for both clinicians and patients have increased as identified through correlation value (+0.869 and 0.288 respectively). Unplanned visits have been reduced after integrating DHI services in healthcare (correlation: =0.835). Moreover, the p-value is less than 0.001 which suggests that, after implementing DHI, the patients started to consult with the doctor before visiting the hospital.

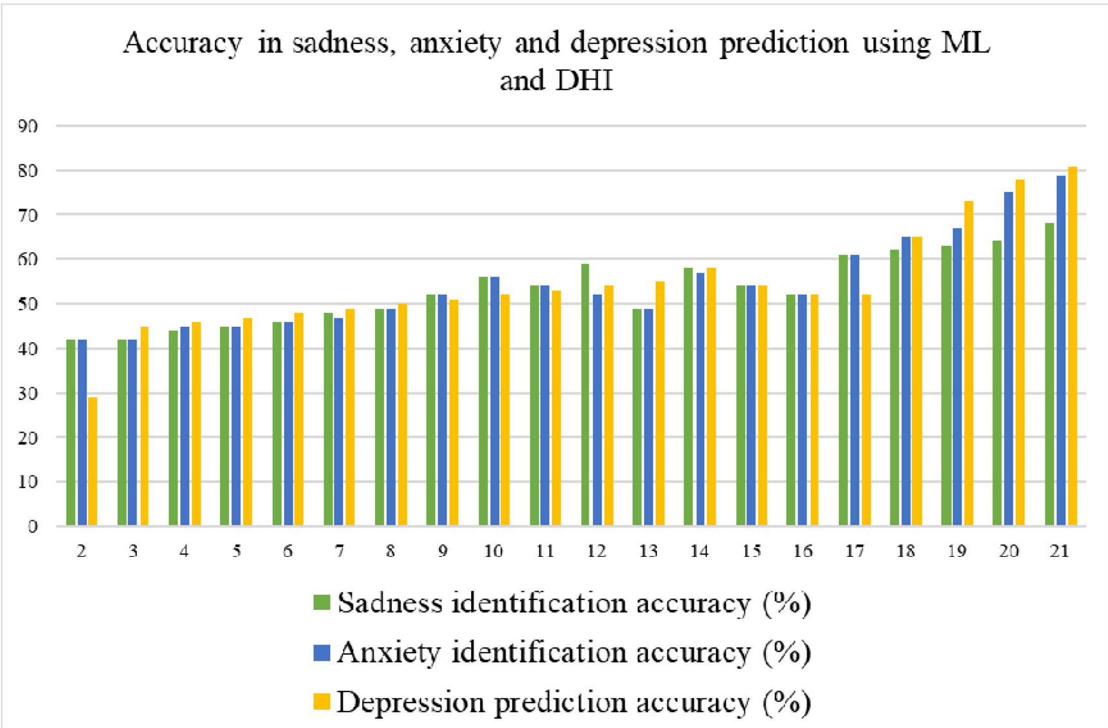

Figure 4: Accuracy increases in psychological illness prediction after several months of ML and DHI practice

TABLE II. DESCRIPTIVE STATISTICS OUTPUT

Statistics								
		Months of ML use for DHI	**Sadness identification accuracy (%)**	**Anxiety identification accuracy (%)**	**Depression prediction accuracy (%)**	**patient's satisfaction on DHI**	**Clinician's satisfaction on DHI**	**Unplanned hospital visit (%)**
N	Valid	20	20	20	20	20	20	20
	Missing	0	0	0	0	0	0	0
Mean		11.50	53.40	54.45	54.60	4.80	4.55	61.00
Median		11.50	53.00	52.00	52.00	5.00	4.50	62.00
Std. Deviation		5.916	7.796	10.359	11.953	1.824	1.849	17.257
Minimum		2	42	42	29	1	1	23
Maximum		21	68	79	81	7	7	83
Percentiles	95	20.95	67.80	78.80	80.85	7.00	7.00	82.95

Table II shows the value of the descriptive statistics where it can be observed that clinicians and patients have been selected, who used ML and DHI for a maximum of 21 months and a minimum of 2 months. The highest accuracy in sadness identification is 68%; anxiety identification is 79%, and depression prediction is 81%. The Likert scale of satisfaction is 1-7 where both clinicians and patients have been satisfied by more than average (4.5-5). Before ML and DHI practice, more than 83% of unplanned hospital visits were observed and after the practice, the unplanned visits were reduced to 23%. Concerning this, Figure 5 shows the reduction in unplanned hospital visits by the patients.

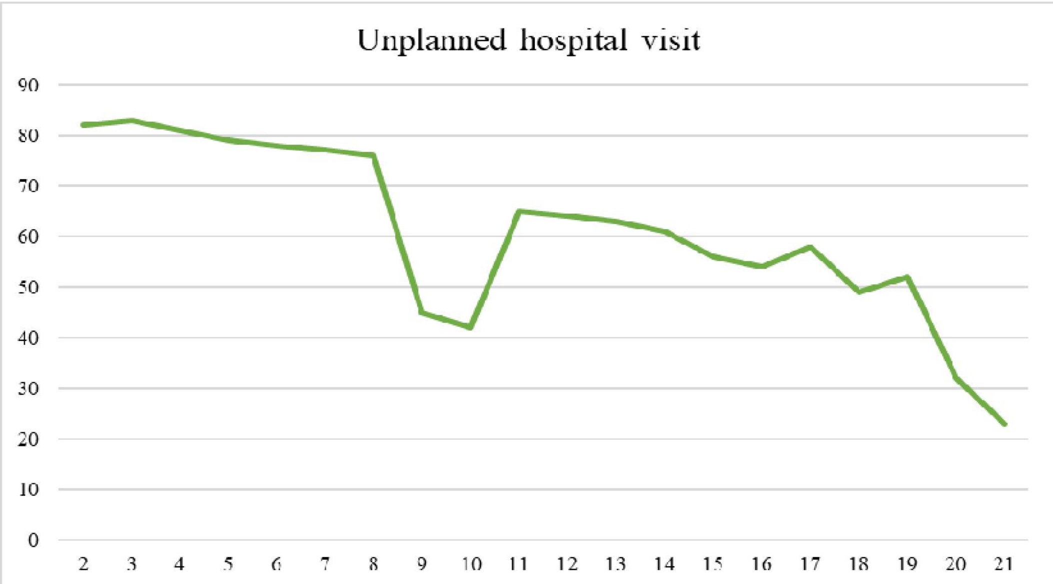

Figure 5: Reduction in an unplanned hospital visit

TABLE III. REGRESSION COEFFICIENT OUTPUT SHOWING THE IMPACT OF INDEPENDENT VARIABLES ON CLINICIANS' SATISFACTION

Coefficients a			
Model		**t**	**Sig.**
1	(Constant)	-1.866	.082
	Sadness identification accuracy (%)	1.141	.272
	Anxiety identification accuracy (%)	.303	.766
	Depression prediction accuracy (%)	1.374	.190
	Unplanned hospital visit (%)	1.063	.304
a. Dependent Variable: Clinician's satisfaction on DHI			

Table III shows that clinician's satisfaction is strongly significant with the unplanned hospital visits and accuracy in psychotherapy. However, the positive t values suggest the independent variables positively impacted the satisfaction level of clinicians. On the contrary of individual p-value, ANOVA table 4 shows the entire regression model is statistically significant ($p<0.001$; $F=10.208$). Therefore, it can be interpreted that the independent variables positively impacted the satisfaction level of clinicians.

TABLE IV. ANOVA OUTPUT SHOWING THE F AND P-VALUE

ANOVA [a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	47.501	4	11.875	10.208	.000[b]
	Residual	17.449	15	1.163		
	Total	64.950	19			
a. Dependent Variable: Clinician's satisfaction on DHI						
b. Predictors: (Constant), Unplanned hospital visit (%), Depression prediction accuracy (%), Sadness identification accuracy (%), Anxiety identification accuracy (%)						

DISCUSSION AND FINDINGS

The analysis has found that clinicians are satisfied with the use of ML and Digital intervention for patient care. When the analysis was carried out from the clinician's perspective, it has been observed that clinicians have been benefited in predicting the anxiety, depression and sadness of patients through digital intervention and by the help of machine learning techniques. It ultimately increased the satisfaction level of clinicians ($p<0.001$). Other studies have shown that ML helped stroke prediction by analysing various biomarkers and it showed more accuracy than conventional risk assessment [15]. On the other hand, patients did not show consistency in satisfaction level. The satisfaction levels of patients fluctuated ($p>0.2$) which suggest that different patients obtained differences in the digital intervention (Figure 6). As by the study Ross and colleagues showed, the digital intervention requires the involvement of more than one clinician sometimes. For example, nurses are also required for the diabetes patients to provide real-time cases; however, it was not possible for every time which probably affected the patient's satisfaction [16].

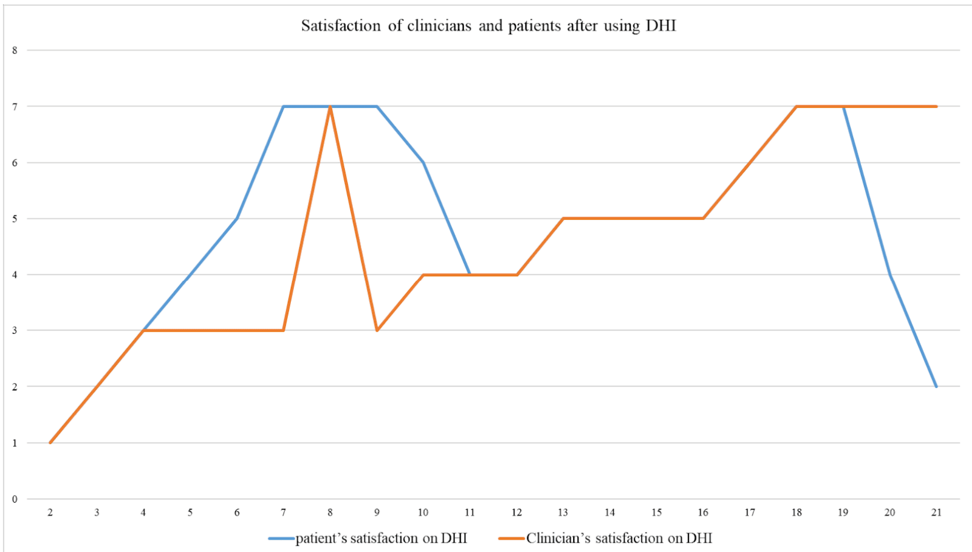

Figure 6: Fluctuation in satisfaction level

Clinicians have been satisfied with the digital intervention and use of ML because they obtained a treatment schedule for the patients. Previously, unplanned visits of patients were observable which provided an urgent treatment requirement; however, after the clinicians have contacted the patient digitally, treatment was scheduled. It ultimately satisfied the clinicians. Research by Latchoumi and co-researchers showed that clinicians can easily obtain the data of family history, blood pressure measurement, weight, height, age, BMI, pregnancy, and abortion via a digital platform and can analyse by using ML architectures [17]. Thereafter, the patient's current citation is explained via DHI and treatment is scheduled accordingly [18,19].

Concerning this, studies with ML showed that ML algorithms are approximately 78% accurate and by effective training, the accuracy can be improved to 98% [20]. Therefore, the use of ML and DHI truly helped the clinicians; however, DHI needs to be improved from the perception of patients [21,22].

CONCLUSION

The research has been carried out with 300 individuals (150 clinicians and 150 patients) who have been using ML for 2-21 months. The satisfaction level of clinicians and patients have been identified. It was observed that clinicians are satisfied with using machine learning and Digital health intervention. However, patients' satisfaction levels were fluctuating due to not having effective interactions with the clinicians. Clinicians have obtained a significant improvement in the accuracy of anxiety, depression and sadness prediction through DHI. After the implementation of DHI, patients negotiated with the clinicians for the hospital visit and treatments which helped the clinicians to schedule their treatment. Various advantages have been observed from this; however, during DHI, security and privacy might become a concern that needs to be addressed.

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