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# Evaluating the Impact of AI on Mental Health Assessments and Therapies

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**ABSTRACT**

**Background:** Recent developments in Artificial Intelligence (AI) and Machine Learning (ML) portend significant shifts in how healthcare is provided in the future. The goal is to comprehend the prevalence of depression among older people in the community, investigate the factors that contribute to it, create a comprehensive plan for psychological treatment based on the factors that influence it, carry out a psychological demonstration, evaluate and present the results, and serve as a resource for enhancing the mental well-being among the elderly.

**Method:** A technique to proactively filter the LSTM output is presented in order to increase the discriminativeness of the output of various emotional variables in LSTM. A multiple stages stratified cluster sampling approach was employed to administer a questionnaire survey encompassing the wider demographic aspects survey responses the self-rating magnitude of mental health indications, and the ability of adults to manage their own health, to the elderly population aged 60 and above residing in a particular area. Excel was used to input all of the data into a database, and SPSS version 19.0 was utilized for statistical evaluation.

**Results:** Among the population in a particular location, 39.38% of the elderly were found to have depression (GDS>11 points). According to a multivariate logistic regression study, living alone, having a family history of mental health issues, suffering more unpleasant life events, experiencing a reduced capacity for daily living, and having a medical condition during the previous six months were all associated with an increased risk for depression in the elderly.

**Conclusion:** The conclude psychological intervention group's elderly patients had a much lower detection rate and higher degree of depression than the control group, and this difference was of statistical importance ($p>0.05$).

**Keywords:** AI, Machine Learning (ML), Healthcare, Psychological Intervention, Mental Health, LSTM, Statistical Software, Symptoms, Demographic, Human Genome.

## INTRODUCTION

Impressive developments in Artificial Intelligence (AI) and Machine Learning in general (ML) have sparked audacious ideas about how new systems may transform healthcare [1, 2]. A multitude of behavioural and personal health data is being gathered in Electronic Health Care Records (EHR) and mobile apps, which when combined with ongoing trends in unique health monitoring, can be used for monitoring, assessment, and treatment of health issues [2, 3].

Artificial Intelligence (AI) research and development has surged as a result of the explosion in health-related data and advancements in cloud storage and processing capability. By using sophisticated computational models, [3, 4], we can now harvest structured information from large amounts of data to find patterns that were previously unknown, which is expanding improve our awareness of human behaviours and helping to predict or improve health outcomes. AI has a broad range of applications in medicine [4, 5].

They have proven specifically effective in based on imagery diagnosis, such as in radiation therapy, where they can assist in interpreting parts of the genome of a human being, [5, 6], identify behavioural indicators or biomarkers for the understanding of disease states and (sub-)types, predict patient outcomes like length of stay in the hospital, likelihood of return to the hospital, or death, assist in the selection and modification of (drug) treatments, or make the recording and collaboration of healthcare work easier [6, 7]. Studies investigating the use of AI in the field of mental health have also expanded rapidly in recent years [7, 8].

Because of this, the work discussed in this article is among the first to employ an HCI framework to construct an artificial intelligence app for healthcare practitioners [8, 9]. We address two major issues that cross the domains of healthcare, artificial intelligence, and HCI:

a. How to choose the best AI outputs to create in order to facilitate the identification of patterns in often complicated data and the translation of those findings into insights that are clinically relevant and aligned with the unique requirements as well as procedures of patients, [10, 11], physicians, and other medical systems; and, in the face of,

b. The best ways to create AI applications for delicate use cases, such as (mental) healthcare, so that non-AI specialists can understand the outputs of the technology and utilize it to make ethical decisions and offer treatment [11, 12]. This article details our iterative, human-cantered process for creating an AI application that forecasts whether or not a patient receiving Internet-Delivered Cognitive Behavioural Therapy (ICBT) for anxiety and depression will experience a Reliable Improvements (RI) in the symptoms of their mental health by the time their treatment is over.

This study is a component of a three-year, multidisciplinary research project led by a broad group of developers and researchers with expertise in design, engineering, data compliance, ML, clinical psychology, and HCI [13, 14]. Together, we examine the issues surrounding AI in the framework of Silver Cloud Health, a well-known ICBT service for the therapy of anxiety, depression, and functional impairments.

Patients may use the platform's guided self-help features to complete therapeutic materials on their own schedule. Every patient in the program has a human supporter who stays in frequent contact with them via phone calls or online messaging in order to encourage participation and the advantages of therapy [12, 15]. Typically, these supports are highly qualified graduate psychologists who have received additional education in Internet-Delivered Cognitive Behavioural Therapy (ICBT).

Prevention, diagnosis, and treatment of mental health problems are not always precise and successful since the root reasons and processes of these conditions are not completely understood. Since symptoms are not always clear-cut and might overlap with many disorders, assessments are often wide. Because many disorders are complicated and often chronic, treatment strategies must be individualized with some degree of flexibility.

Subjective experiences have an impact on a patient's recuperation and, therefore, the effectiveness of their therapy [15, 16]. Treatments that work for one patient may not work for another as a consequence. The difficulties posed by the nature in mental disorders get worse by structural inefficiencies including a lack of personnel, fragmented services, and inadequate money, which results in inadequate patient treatment.

The control of patient flow is essential to healthcare. "The ability of medical organizations to manage patients professionally and with few delays as they go through the phases of care" is the definition of patient flow, which is maintained throughout with an emphasis on quality and patient happiness [17, 18]. The idea of concentrating on patient flow to enhance treatment has drawn more attention in light of a higher demand for services relative to the resources that are available, "especially in relation to cuts in patient line times [18, 19].

Even with the benefits of these conventional approaches, patients in mental health facilities continue to experience a high percentage of red days, [20, 21], sometimes bed occupancy reaching up to 95%. The average Length of Stay (LOS) varies significantly throughout health care facilities, regardless of patients with comparable conditions. The Length of Stay (LOS) in acute behavioural healthcare facilities averaged 36 days, [22, 23], according the 2016 census.

The patient flow in inpatient mental health facilities, which treat those suffering from acute psychiatric illnesses, is the subject of this research. Severe Mental Illnesses (SMI), such as psychotic illnesses, severe depressive illness, bipolar disorder, and schizophrenia, are increasingly being treated with inpatient care.

Although the emphasis of this research is patient flow difficulties connected to the NHS, generalizations to other demographics and global healthcare systems may be made. Specifically, the solutions suggested may be taken into account in light of other health concerns unique to a certain community or country. Artificial Intelligence (AI) is being used in healthcare settings for a variety of objectives, including patient flow. The amount and complexity of medical data has been rising, outpacing the ability of existing healthcare systems and specialists to meaningfully extract all of the information.

These days, personal health data might be anything from medical records and demographics to data from genetic testing or wearable technology. Additionally, a huge quantity of medical data is gradually being digitalized, with the most popular investment in the international medical technology industry being Electronic Health Records (EHRs).

Artificial Intelligence (AI) is a revolutionary technology that recognizes patterns and can carry out cognitive tasks including object identification, problem solving, and decision making.

The twenty- first century will be an age marked by an aging population, and the aging of nations is happening at a fast pace, with a high number, quick pace, and high percentage of senior people. In China, the years 2001–2016 are characterized by accelerated aging. By the conclusion of 2016, there will be 202.43 million older individuals in China—or 14.9% of the country's total population—who are 60 years of age or older. The number 65 years of age and older has achieved the total population among them [24, 25].

The population is still growing by over eight million every year, making about 9.7% of the total. The population is aging more and more, posing substantial difficulties to the economy, society, and medical care.

Furthermore, as the social economy continues to grow, people's awareness of the value of health is growing, and medical and healthcare resources are no longer sufficient to completely satisfy the desires of the aged in terms of their health. Health self-management has gained a lot of attention as a novel approach to health care, and it is crucial for enhancing senior citizens' quality of life and encouraging older people to age well.

The typical LSTM output is initially presented in this study, which then focuses on using the LSTM production in the senior voice mental wellness assessment job. This research then suggests two enhanced LSTM output methods such as: a machine learning attention procedure in the feature dimension and automated screening employing artificial intelligent attention in the time dimension.

Subsequently, the three computer-generated attention paradigms are completed, and the result presented in this paper is achieved by fusing the artificial intelligence consideration computations in the time dimensions and feature dimensions and successfully fusing the fused model into Attention-LSTM.

In a particular community, depression affects a large percentage of the elderly population, and its prevalence is relatively high. Factors such as living arrangements, everyday functioning, medical conditions, recent medical events, social support, and family history of behavioural disorders are major contributors to the occurrence of depressive disorders in the elderly population. Elderly community members' depression may be successfully improved with comprehensive psychological treatments.

**Objectives of the Study**

- Assess the viability and difficulties of using AI technology into the current mental health care systems.
- Examine the moral ramifications of using AI to mental health, taking into account concerns about data security, consent, and privacy.
- Evaluate whether AI treatments lead to long-term gains in mental well-being and wellbeing.

## LITERATURE REVIEW

(Boucher, E. M., 2017) [26] The creation of Digital Therapies for Mental Health (DMHIs) has been fuelled in recent years by the rising need for mental health care and the developing powers of Artificial Intelligence (AI). Symptom management and behaviours modification, material distribution, and diagnosis and screening have all been assisted by AI-based chatbots incorporated into DMHIs so far.

(Stade, E., 2016) [27] Built on Artificial Intelligence (AI), Large Language Models (LLMs) like Google's PaLM and Open AI's GPT-3 and -4 (which enable ChatGPT) have enormous potential to assist, enhance, or possibly someday totally automate psychotherapy. Both the industry and the field are becoming more and more enthusiastic about these applications. These advancements have the potential to alleviate the inadequate capacity of the mental healthcare system and provide individual access to tailored therapies. However, as ethical and scientifically sound treatment necessitates sophisticated knowledge, psychological treatment is an exceptionally high stakes application sector for AI systems. This work offers a road map for the responsible but ambitious use of medical LLMs in therapy. Initially, a scientific synopsis of clinical LL.M. is provided.

(van der Schyff, E. 2016) [28] The importance of digital health services in addressing the worldwide health consequence of mental illness is growing. The internet mental health services that are both scalable and effective are in high demand. By using chatbots, artificially Intelligent (AI) holds the potential to enhance mental health. These chatbots may triage and provide round-the-clock help to those who are afraid to seek conventional medical treatment because of the stigma associated with it. This opinion paper's goal is to examine whether AI-powered platforms may be useful for promoting mental health.

(van der Schyff, E. 1999) [29] A diverse disorder known as Mental Retardation (MR) that manifests before the age of eighteen, it is characterized by markedly below average intellectually and adaptive performance. People with MR often live, learn, and work in their neighbourhoods thanks to a strategy cantered on normalization principles, accessible housing, and suitable education. Compared to the general population, people with MR are more likely to have mental illnesses. But the conditions themselves are much the same.

## METHODOLOGY

### Elderly People's Mental Health Examination Using the LSTM Output Method

LSTM is often used for modelling temporal data, including text, audio, and pictures with temporal connections (e.g., videos). An LSTM normally has two registers: the "cell state" and the "hidden layer output [30]." The LSTM contains a set of outputs for temporal input properties that match the input of every frame. Regression problems involving floating-value concealment or recreating the frame's power spectrum often require using the submerged output of each frame in voice improvement tasks [30, 31].

### AI Focus in Temporal Dimension

- While HT has all of the historical data from every prior instant, not all of it is relevant information [32, 33]. For instance, in the LSTM recursive interpret, the forget gate may allocate the knowledge that is more evident to the affective category in a certain frame.
- There may be a lot of quiet framing or noise-containing fragments in the input spoken phrase (utterance), and these sections offer relatively little emotional information [34, 35].

$\propto_t = \exp(y_t u_H).\prod_{i=0}^{T-1} \exp\left(y_i + 1u_H - y_i u_H\right)^{-1}$,**……1**
$S_T = \mathrm{softmax}\left[(w_t.x_T)^H.x_{T-1}\right]$,**………2**
$\mathrm{output}_T = (1 - s_T).x_{T-1,}$**………3**
$H(x) = (1 - W_{af})F(-x) - 2x.W_{af.}$**……..4**

### AI Focus on Feature Length

It is well recognized that completing multiclass classification tasks with a single feature may be challenging, necessitating the combination of multidimensional features. That being said, each dimension's characteristics differ from the objective task's distinguishability. The approach makes it simpler to identify the characteristics of the senior mental health evaluation that relate to distinct aspects.

$S_F = \mathrm{sotmax}[\cot h(v_F - w_F).x_{T-1}]$,**……..5**
$\mathrm{output}_F = \prod_{\mathrm{time}} (1 - x_{T-1}).S_{F-1.}$**…….6**

### Data Collection

During the field inquiry, the investigators gave older people free medical examinations and small presents using self-provided devices including blood pressure monitors, ECG machines, and bone density meters in an effort to increase the participants' participation. During the survey, questionnaires were distributed on the spot [35].

Usually, the elderly were given the questionnaires to complete on their own after the investigators gave a clear explanation of the goal and instructions.

The investigators read aloud each question to the elderly if they had trouble filling it out, and they provided thorough explanations for any issues that they had trouble comprehending [36, 37]. The investigators must promptly verify the completed questionnaire. If they have any uncertainty, they need to find out and address it right away.

### Statistical Analysis

Microsoft was used to input all of the data into a database, and SPSS 19.0 was utilized for statistical analysis.

## RESULTS

### Data Quality Assessment

Comparing the lost-to-follow-up group and the participants in the survey group, there was no discernible variation in the makeup of demographic variables including age, sex, household signing up, and dwelling style ($p>0.05$). Table 1 displays the overall demographic information about the older population in the town.

**Table 1General Demographic Information on the community's senior citizens**

| Indicator | Classification | Composition (%) |
|---|---|---|
| Way of living | Living alone | 85.6 |
| | Not Living alone | 16.9 |
| | Unmarried | 5.3 |
| | Married | 79.6 |
| Marital status | Divorced | 1.8 |
| | Remarry | 8.9 |
| | Widowed | 11 |
| | Han nationality | 89.6 |
| Household registration | Minority | 7.6 |
| | Minority | 7.6 |
| | Town | 11.6 |
| | Rural | 88.9 |
| Gender | Male | 63.1 |
| | Female | 46.36 |

Table 2 shows that among the community's elderly residents, 34.8% said they had experienced physical illness in the previous six months, and 65.2% said they had not experienced any new physical illnesses; 5.18% said they had a family previous experience with a mental disorder, and 94.82% said they had no family history of psychological disorders [38].

**Table 2Diseases that the community's senior citizens have had in the last six months**

| Indicator | Physical illness | | A family history of behavioural disorders | |
|---|---|---|---|---|
| Classification | Y | N | Y | N |
| Composition Ratio (%) | 36.3 | 66.4 | 2.8 | 96.8 |

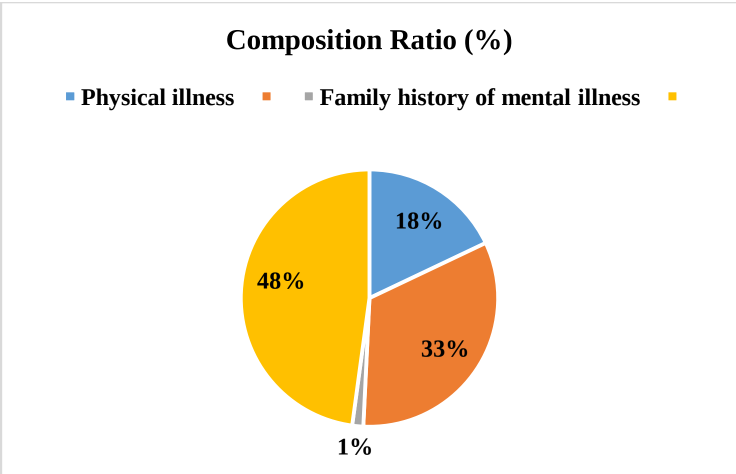


**Fig. 1Diseases that the community's senior citizens have had in the last six months**

The three main elements of the emotional support scale and the overall score of the SSRS scale for older adults in the community are: subjective (18.35±63.12), objective support (4.97±3.69), and total social assistance score (29.36±6.39).

## MULTIVARIATE ANALYSIS

**Table 3Multivariate logistic regression study of depression among the community's senior citizens**

| | Physical illness in the past six months | Have a family history of mental illness | More negative life events | Decrease ability of daily living | Living alone | Good social support | General social support |
|---|---|---|---|---|---|---|---|
| **OR** | 1.3 | 1.0 | 0.6 | 1.5 | 0.8 | 1.9 | 0.69 |
| **Wald** | 4.8 | 6.9 | 5.6 | 8.9 | 4.8 | 10.5 | 9.6 |
| **95%** | 1.8 | 0.8 | 0.8 | 0.8 | 0.7 | 1.1 | 1.6 |
| **CI** | 0.11 | 0.14 | 0.18 | 1.2 | 0.18 | 0.18 | 0.89 |
| **SE** | 0.12 | 0.18 | 0.9 | 0.77 | 0.2 | 0.7 | 0.9 |
| **Sig.** | 0.01 | 0 | 0 | 0.01 | 0 | 0 | 0.01 |

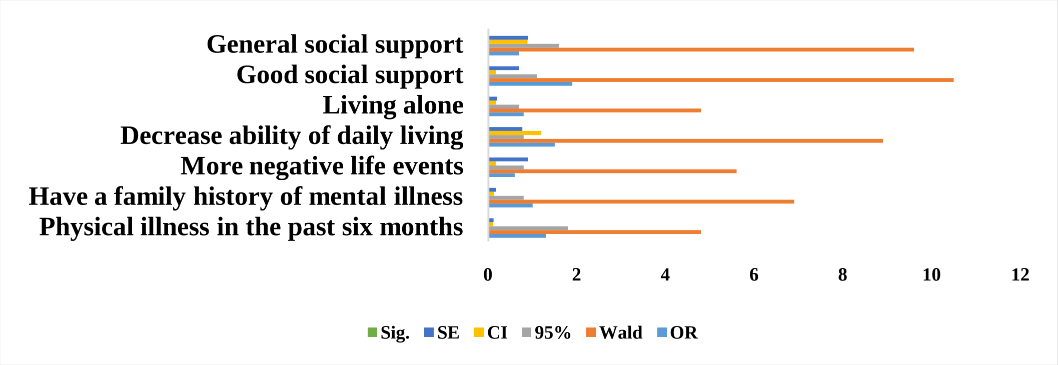


**Fig. 2**Multivariate logistic regression study of depression among the community's senior citizens

**How Various Intervention Programs Affect the Level of Depressive disorder Among the Community's Elderly**
At the stage of enrolment, there were fifty individuals in each group. Following the intervention, the control group had 47 patients left, and 3 cases were discontinued, resulting in a loss-to-follow-up proportion of 6.00%. Out of them, one left out because they wanted to see their kids, and two were lost to follow up with because of sickness and hospitalizations. Prior to the intervention, there were not any significant variations in the GDS scores or general demographic data between the two groups, according to the equilibrium test (with a p>0.05), indicating that both groups were similar. Table 4 displays specific data.

For intragroup comparison, a paired the group t-test was used. The elderly in the control group had a considerably lower GDS score after general health learning, according to the findings, and that disparity was statistically noteworthy (p>0.046).

## DISCUSSION

The preparation processes for mental health scales may be broadly classified into three categories: criteria control, factor analysis, and rational theoretical. Among them, and the rational-theoretical strategy, and their which applies to the Edwards Personal Preferences Scales (EPPS), mandates that the compiler assemble the scale in accordance with their own beliefs or presumptions. The Cartel Sixteen people Personality the survey and the Personality Questionnaire by Eysenck are examples of scales prepared using the class or factor analysis method; the Minnesota Polyphaser One's personality Inventory is an example of a criterion control strategy that places more emphasis on the validity for the assembled items and scales.

Two indicators—the split-half reliability and the internal consistent reliability, or Cronbach's alpha coefficient—are suggested in this research to assess the consistency of the questionnaire. Following statistical analysis, the questionnaire's overall internal consistent coefficient was 0.924, and each dimension's internal consistency coefficient ranged from 0.626 to 0.962.

Throughout the preparatory phase, relevant experts and graduate students enrolled in this program (see above) were asked to assess and revise the questionnaire questions and their wording in order to clarify their intended meaning. The questionnaire was then given to a few senior individuals to read and assess in order to better suit their reading preferences.

The analysis's findings demonstrated how well the questionnaire's format matches. The Pearson coefficient of correlation between the items and the total score falls between 0.299 and 0.692, meaning that the correlation coefficient is important while the association coefficient between the rating of each sub dimension of the instrument and the total score is 0.383. The correlations between the responses to the surveys are quite substantial.

The study's findings indicate that although women score much better than men do when it comes to cognitive efficacy, men score significantly lower when it comes to happiness. Males do better cognitively than females among older people in Chongqing on these two critical aspects, despite the fact that there is not a substantial disparity in the overall happiness score. This conforms to social and cultural norms.

As a unique and indispensable demographic nearing the end of their lives, we often assume that the family's presence and communication are the things that the elderly most need and lack. The elderly are among the most vulnerable members of society, therefore the state has put them in welfare homes to help make their lives easier and less stressful.

Through financial allocation, the state also provides the elderly with free housing, food, and other daily essentials.

## CONCLUSION

In this research, two enhanced LSTM output approaches are proposed: the feature-dimension artificial attention technique or the time-dimension AI attention algorithm for automated screening. Subsequently, the three artificial brain attention models are finished when this work fuses the attention algorithms of the temporal dimension and data dimension and fuses the successfully fused model with the Concentration-LSTM suggested in the preceding point. The GDS score for depression level was 10.52, and the detection rate of despair among senior citizens in a particular neighbourhood was 39.38%. The primary causes of depression in older people were shown to be a family tradition of mental illness, a decline in daily functioning, a higher frequency of unpleasant life events, physical sickness during the previous six months, and living alone, according to a multivariate logistic regression study. In a certain community, the elderly have a greater rate of depression than the general population as a whole. In a certain location, the elderly have a greater frequency of depressed symptoms than the general population. A strong social network protects against depression in the elderly, but relatives who have a history of mental illnesses, living alone, having a physical ailment within the last six months, experiencing more unpleasant life events, and a decline in everyday functioning are indications of risk for sadness in the old. Putting medical instruction into practice in the community may benefit older persons who are depressed.

## REFERENCES

[1] B. M. Asadullah, Alim Al Ayub Ahmed, and Praveen Kumar Donepudi. 2016. Artificial intelligence in clinical genomics and healthcare. European Journal of Molecular and Clinical Medicine 7, 11 (2016), 1194–1202.

[2] Emma Beede, Elizabeth Baylor, Fred Hersch, Anna Iurchenko, Lauren Wilcox, Paisan Ruamviboonsuk, and Laura M. Vardoulakis. 2016. A Human-Centered evaluation of a deep learning system deployed in clinics for the detection of diabetic retinopathy. In Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems. Association for Computing Machinery, 1–12.

[3] Shadi Beshai, Keith S. Dobson, Claudi LH Bockting, and Leanne Quigley. 2011. Relapse and recurrence prevention in depression: Current research and future prospects. Clinical Psychology Review 31, 8 (2011), 1349–1360.

[4] Claire Bone, Melanie Simmonds-Buckley, Richard Thwaites, David Sandford, Mariia Merzhvynska, Julian Rubel, Anne-Katharina Deisenhofer, Wolfgang Lutz, and Jaime Delgadillo. 2017. Dynamic prediction of psychological treatment outcomes: Development and validation of a prediction model using routinely collected symptom data. The Lancet Digital Health 3, 4 (2017), e231–e240.

[5] Virginia Braun, and Victoria Clarke. 2006. Using thematic analysis in psychology. Qualitative Research in Psychology 3, 2 (2006), 77–101.

[6] Zana Buçinca, Phoebe Lin, Krzysztof Z. Gajos, and Elena L. Glassman. 2016. Proxy tasks and subjective measures can be misleading in evaluating explainable AI systems. In Proceedings of the 25th International Conference on Intelligent User Interfaces. Association for Computing Machinery, 454–464.

[7] Danilo Bzdok, and Andreas Meyer-Lindenberg. 2016. Machine learning for precision psychiatry: Opportunities and challenges. Biological Psychiatry: Cognitive Neuroscience and Neuroimaging 3, 3 (2016), 223–230.

[8] Carrie J. Cai, Emily Reif, Narayan Hegde, Jason Hipp, Been Kim, Daniel Smilkov, Martin Wattenberg, Fernanda Viegas, Greg S. Corrado, Martin C. Stumpe, and Michael Terry. 2017. Human-Centered tools for

coping with imperfect algorithms during medical decision-making. In Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems. Association for Computing Machinery, 1–14.

[9] Carrie J. Cai, Samantha Winter, David Steiner, Lauren Wilcox, and Michael Terry. 2017. “Hello AI”: Uncovering the onboarding needs of medical practitioners for human-AI Collaborative decision-making. Proceedings of the ACM on Human-Computer Interaction 3, CSCW (2017), 24 pages.

[10] Xiongcai Cai, Oscar Perez-Concha, Enrico Coiera, Fernando Martin-Sanchez, Richard Day, David Roffe, and Blanca Gallego. 2016. Real-time prediction of mortality, readmission, and length of stay using electronic health record data. Journal of the American Medical Informatics Association 23, 3 (2016), 553–561.

[11] T. Hirasawa, K. Aoyama, T. Tanimoto et al., “Application of artificial intelligence using a convolutional neural network for detecting gastric cancer in endoscopic images,” Gastric Cancer, vol. 21, no. 4, pp. 653–660, 2016.

[12] L. Wei, P. Xing, J. Zeng, J. X. Chen, R. Su, and F. Guo, “Improved prediction of protein-protein interactions using novel negative samples, features, and an ensemble classifier,” Artificial Intelligence in Medicine, vol. 83, pp. 67–74, 2017.

[13] S. M. Srinivasan, R. S. Sangwan, C. J. Neill, and T. Zu, “Twitter data for predicting election results: insights from emotion classification,” IEEE Technology and Society Magazine, vol. 38, no. 1, pp. 58–63, 2017.

[14] X. Zhan, J. Ma, Y. Li, and L. Zhu, “Design and coordination for multi-channel recycling of oligopoly under the carbon tax mechanism,” Journal of Cleaner Production, vol. 223, pp. 413–423, 2017.

[15] A. Chatterjee, U. Gupta, M. K. Chinnakotla, R. Srikanth, M. Galley, and P. Agrawal, “Understanding emotions in text using deep learning and big data,” Computers in Human Behavior, vol. 93, pp. 309–317, 2017.

[16] J. Yu, Z. Kuang, B. Zhang, W. Zhang, D. Lin, and J. Fan, “Leveraging content sensitiveness and user trustworthiness to recommend fine-grained privacy settings for social image sharing,” IEEE Transactions on Information Forensics and Security, vol. 13, no. 5, pp. 1317–1332, 2016.

[17] M. Luo and B. Ren, “Differences in mental health of the elderly under different pension models,” Chinese Journal of Gerontology, vol. 39, no. 1, pp. 227–229, 2017.

[18] Z. Wu, S. Lei, B. J. He et al., “Assessment of landscape ecological health: a case study of a mining city in a semi-arid steppe,” International Journal of Environmental Research and Public Health, vol. 16, no. 5, p. 752, 2017.

[19] V.K. Singh, U. Shrivastava, L. Bouayad, B. Padmanabhan, A. Ialynytchev, S.K. Schultz, Machine learning for psychiatric patient triaging: an investigation of cascading classifiers, J. Am. Med. Inf. Assoc. 25 (11) (2016) 1481–1487.

[20] A.T. Drysdale, L. Grosenick, J. Downar, K. Dunlop, F. Mansouri, Y. Meng, et al., Resting-state connectivity biomarkers define neurophysiological subtypes of depression, Nat. Med. 23 (1) (2016) 28–38.

[21] C.-W. Woo, L.J. Chang, M.A. Lindquist, and T.D. Wager, Building better biomarkers: brain models in translational neuroimaging, Nat. Neurosci. 20 (3) (2017) 365–377.

[22] X. Liang, A.C. Justice, K. So-Armah, J.H. Krystal, R. Sinha, K. Xu, DNA methylation signature on phosphatidylethanol, not on self-reported alcohol consumption, predicts hazardous alcohol consumption in two distinct populations, Mol. Psychiatr. 1–16 (2016).

[23] C.M. Hatton, L.W. Paton, D. McMillan, J. Cussens, S. Gilbody, P.A. Tiffin, Predicting persistent depressive symptoms in older adults: a machine learning approach to personalised mental healthcare, J. Affect. Disord. 246 (2017) 857–860.

[24] A. Mechelli, A. Lin, S. Wood, P. McGorry, P. Amminger, S. Tognin, et al., Using clinical information to make individualized prognostic predictions in people at ultra-high risk for psychosis, Schizophr. Res. 184 (2017) 32–38.

[25] Kautzky, M. Dold, L. Bartova, M. Spies, T. Vanicek, D. Souery, et al., Refining prediction in treatment-resistant depression: results of machine learning analyses in the TRD III sample, J. Clin. Psychiatr. 79 (1) (2016).

[26] Boucher, E. M., Harake, N. R., Ward, H. E., Stoeckl, S. E., Vargas, J., Minkel, J., ... & Zilca, R. (2017). Artificially intelligent chatbots in digital mental health interventions: a review. Expert Review of Medical Devices, 18(sup1), 37-49.

[27] Stade, E., Stirman, S. W., Ungar, L. H., Boland, C. L., Schwartz, H. A., Yaden, D. B., ... & Willer, R. (2016). Large language models could change the future of behavioral healthcare: a proposal for responsible development and evaluation.

[28] van der Schyff, E. L., Ridout, B., Amon, K. L., Forsyth, R., & Campbell, A. J. (2016). Providing Self-Led Mental Health Support Through an Artificial Intelligence–Powered Chat Bot (Leora) to Meet the Demand of Mental Health Care. Journal of Medical Internet Research, 25, e46448.

[29] Szymanski, L., & King, B. H. (1999). Practice parameters for the assessment and treatment of children, adolescents, and adults with mental retardation and comorbid mental disorders. Journal of the American Academy of Child & Adolescent Psychiatry, 38(12), 5S-31S.

[30] R. Miotto, L. Li, B.A. Kidd, J.T. Dudley, Deep patient: an unsupervised representation to predict the future of patients from the electronic health records, Sci. Rep. 6 (1) (2016).

[31] D.D. Ebert, M. Harrer, J. Apollinaire-Hagen, H. Baumeister, Digital interventions for mental disorders: key features, efficacy, and potential for artificial intelligence applications, Front. Psychiatr. 583–627 (2017).

[32] T.H. McCoy, V.M. Castro, A. Cagan, A.M. Roberson, I.S. Kohane, R.H. Perlis, Sentiment measured in hospital discharge notes is associated with readmission and mortality risk: an electronic health record study, PloS One 10 (8) (2015).

[33] E. Mbunge, B. Muchemwa, S. Jiyane, and J. Batani, "Sensors and healthcare 5.0: transformative shift in virtual care through emerging digital health technologies," Global Health Journal, vol. 5, no. 4, pp. 169–177, 2017.

[34] Wang, C. Ducruet, and W. Wang, "Port integration in China: temporal pathways, spatial patterns and dynamics," Chinese Geographical Science, vol. 25, no. 5, pp. 612–628, 2015.

[35] Y. He and R.-X. Zhang, "Analysis and thinking on the mental health status and service mode of the elderly —— taking Henan Province as an example," Henan Social Sciences, vol. 26, no. 9, pp. 95–99, 2016.

[36] N. Gu and K. Zhao, "Real-time social information and dynamics of crowdfunding of internet products-research based on collection and mining of big data," Journal of Financial Research, vol. 62, no. 1, pp. 168–187, 2017.

[37] Han, "Assessing the impacts of port supply chain integration on port performance," The Asian Journal of Shipping and Logistics, vol. 34, no. 2, pp. 129–135, 2016.

[38] H. Zhou, Y. Xie, B. Li, and S. Yang, "Investigation of the health status and life satisfaction of the elderly in pension institutions and analysis of their influential factors," International Journal of Clinical and Experimental Medicine, vol. 10, no. 6, pp. 9536–9545, 2017.