WMGPT: Towards 24/7 Online Prime Counseling with ChatGPT

Lismer Andres Caceres Najarro
Korea Institute of Energy Technology
Naju, Republic of Korea
andrescn@kentech.ac.kr

Yonggeon Lee
Korea Institute of Energy Technology
Naju, Republic of Korea
yglee@kentech.ac.kr

Kobiljon E. Toshnazarov
Korea Institute of Energy Technology
Naju, Republic of Korea
qobiljon@kentech.ac.kr

Yoonhyung Jang
BRFrame Inc.
Seoul, Republic of Korea
janga@brframe.com

Hyungsook Kim
Hanyang University
Seoul, Republic of Korea
khsook12@hanyang.ac.kr

Youngtae Noh
Korea Institute of Energy Technology
Naju, Republic of Korea
ytnoh@kentech.ac.kr

ABSTRACT

Traditional in-person counseling encounters limitations in terms of accessibility, flexibility, and social stigma. Additionally, low mental health literacy and embarrassment among individuals hinder help-seeking behavior. Meanwhile, the introduction of more sophisticated sensors embedded in ubiquitous devices such as smartphones and smartwatches, and the release of a powerful large language model, i.e., chatGPT, create new opportunities to address the existing limitations of traditional counseling services. In that regard, we propose *WMGPT*, a system that offers round-the-clock mental health counseling services. By leveraging continuous analysis of user context and digital phenotype, *WMGPT* delivers personalized counseling support. Through 24/7 passive monitoring, it continuously assesses individuals' mental state, initiates conversations on their behalf, and potentially triggers counseling services. These specialized counseling services are facilitated by a fine-tuned chatGPT model. *WMGPT* presents a promising solution to overcome the limitations of traditional counseling by providing accessible, personalized, and timely mental health support, paving the way for a convenient and effective service for improving well-being.

CCS CONCEPTS

• **Human-centered computing → Interactive systems and tools**.

KEYWORDS

ChatGPT, counseling, mental-health, round-the-clock, well-mind

ACM Reference Format:
Lismer Andres Caceres Najarro, Yonggeon Lee, Kobiljon E. Toshnazarov, Yoonhyung Jang, Hyungsook Kim, and Youngtae Noh. 2023. WMGPT: Towards 24/7 Online Prime Counseling with ChatGPT. In *Adjunct Proceedings of the 2023 ACM International Joint Conference on Pervasive and Ubiquitous Computing & the 2023 ACM International Symposium on Wearable Computing (UbiComp/ISWC '23 Adjunct), October 08–12, 2023, Cancun, Quintana Roo, Mexico.* ACM, New York, NY, USA, Article 4, 4 pages. https://doi.org/10.1145/3594739.3610708

UbiComp/ISWC '23 Adjunct, October 08–12, 2023, Cancun, Quintana Roo, Mexico

ACM ISBN 979-8-4007-0200-6/23/10.
https://doi.org/10.1145/3594739.3610708

1 INTRODUCTION

Mental health issues have a significant global prevalence, impacting approximately one in ten people worldwide [5]. However, the current mental health system faces several challenges: On the one hand, the demand for mental health services exceeds the availability of qualified specialists, resulting in a substantial gap in care [2]. On the other hand, traditional in-person counseling is hindered by limitations in accessibility, flexibility, and social stigma. Additionally, factors such as embarrassment, lack of awareness, and societal pressures deter individuals from seeking help, exacerbating the gap between those in need and available services.

In the meantime, recent advancements in technology, such as the integration of sophisticated sensors into ubiquitous devices like smartphones and smartwatches, along with the release of powerful large language models like the chatGPT [12], have opened up new opportunities to address the above mentioned challenges. In light of these opportunities, we introduce *WMGPT*[1], a system that we hope will revolutionize the way mental health services are delivered. By embracing passive monitoring and supporting proactive counseling services, *WMGPT* aims to provide 24/7 online prime counseling, overcoming the barriers associated with traditional in-person counseling. *WMGPT* offers personalized, accessible, and timely mental health support to individuals in need by exploiting digital phenotyping [1], continuous mental state assessment, and chatGPT. In this context, prime counseling implies that the service focuses on addressing immediate mental health needs and providing essential, interventions, strategies, and support by leveraging objective mental health assessment and contextual data of the individual.

Traditional in-person counseling often faces significant accessibility challenges, as individuals may struggle to find suitable counselors in their vicinity or face long wait times for appointments. Additionally, the inflexible scheduling of in-person sessions may not align with the dynamic lifestyles and commitments of individuals seeking counseling. *WMGPT* aims to address these limitations by providing a virtual counseling system that can be accessed anytime, anywhere, ensuring individuals have access to support whenever they need it. Another critical issue that *WMGPT* tackles is the social stigma and embarrassment often associated with seeking mental health assistance [14]. Many individuals hesitate to reach out for help due to fear of judgment or societal pressures. By providing an online counseling system, *WMGPT* offers individuals a safe and confidential space to express their concerns and receive guidance

[1]WMGPT stands for "Well-Mind ChatGPT".

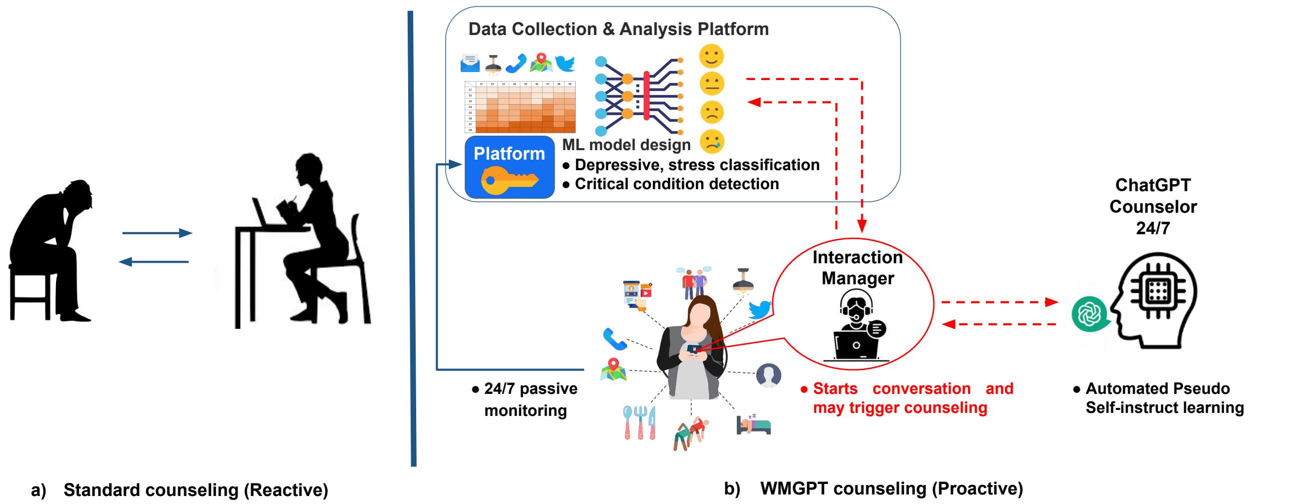

Figure 1: Comparison between standard and proposed counseling service

without fear of stigma. This anonymity can encourage more people to seek the support they require and break down the barriers that prevent individuals from reaching out for help.

Additionally, it is noteworthy that *WMGPT* takes a proactive approach compared to the reactive nature of traditional in-person counseling, see Figure 1. In traditional counseling, sessions only begin when the individual visits a mental health specialist. In contrast, *WMGPT* proactively monitors individuals 24/7 and continuously assesses their mental health through passive monitoring via smartphones and/or smartwatches, see Figure 1-b. Furthermore, by leveraging the power of a specialized chatGPT counselor, timely interventions and counseling support can be provided, allowing proactive care and early intervention when necessary. This approach ensures that individuals receive support even before they actively seek it, promoting better mental well-being and preventing mental crises.

AI based agents are promising solutions in the smart healthcare arena and their applicability is continuously expanding [3, 4, 17]. Although there exist AI-based mental health counseling systems, they do not exploit the passive information of individuals obtained from ubiquitous devices [8, 10, 11]. There lies the novelty of the proposed system *WMGPT*, which represents a significant advancement in the field of mental health counseling. This system aims to bridge the gap between the growing demand for mental health services and the limited availability of specialized counselors, as well as to provide round-the-clock counseling services. Through its accessibility, personalized approach, and round-the-clock availability, we strongly believe that *WMGPT* has the potential to transform the mental health landscape, offering individuals a convenient and effective means to access counseling support and improve their overall well-being.

2 WMGPT COUNSELING SYSTEM

The *WMGPT* is a comprehensive mental health support system that aims to provide 24/7 personalized counseling services by exploiting cutting-edge technologies. Unlike traditional in-person counseling, passive monitoring and proactive counseling posture are integral parts of *WMGPT*. To allow passive monitoring and proactive counseling, *WMGPT* relies on three main components: a passive data collection and analysis platform, interaction manager (IM), and chatGPT counselor, as depicted in Figure 1-b. The platform provides continuous passive monitoring functionality involving the non-intrusive collection of data from individuals and processing it to gain insights into the mental state of each individual. The data collection and analysis platform enables early detection of mental health issues and provides the basis for a proactive intervention. The chatGPT counselor is a chatGPT model fine-tuned with specialized counseling datasets. The IM can be seen as a bridge between three entities, namely, the individual also called user, platform, and chatGPT counselor. In the following, details of these components are provided.

2.1 Data collection and analysis platform

The platform is designed for the purpose of passive data collection pertaining to individuals' behavioral and physiological patterns within their natural environments, leveraging ubiquitous mobile devices such as smartphones and smartwatches. The platform comprises a comprehensive data processing pipeline aimed at detecting stress and depression states. This pipeline encompasses two primary components: continuous monitoring of physiological signals, including heart rate and interbeat intervals, as well as periodic monitoring of behavioral and contextual data. The latter includes variables such as smartphone usage, mobility patterns, posture and motion, and social settings, among others, to enable the detection of symptoms related to stress and depression. Through its systematic and integrated approach, the platform transforms individuals' passive sensing data into objective assessment data on their mental health state, which is eventually relayed to the ChatGPT counselor. In this work, we particularly focus our attention on the detection of stress and depression levels.

Detection of stress levels: The platform utilizes physiological and contextual information retrieved from smartwatches and smartphones, respectively, to detect stress levels. Physiological signals such as heart rates, interbeat intervals, and wrist acceleration are continuously analyzed to capture arousal-related signals associated with stress. Additionally, the smartwatch's acceleration signals help exclude confounding factors from physical activities, distinguishing them from stress-induced responses. Contextual factors of perceived stress are captured using smartphones, including activity recognition, GPS location, screen state, phone calls, and time-related data [18]. These contextual features, combined with physiological data from the smartwatch, create a comprehensive dataset for our machine learning models that finally provides the individual's stress level.

Detection of depression levels: Unlike the detection of stress levels, here we solely utilize data collected from smartphones, capturing digital behavior markers that encompass physical, mental, and social aspects of depression symptoms [7]. Through the platform, we track individuals' daily activities and routines (lifelogging data) to gather contextual information relevant to depressed state. Then our proposed robust data processing pipeline is utilized to classify binary depressed mood labels, i.e., depressed or not depressed. The collected row data is cleaned by excluding erroneous samples and unreliable outliers. Then, in addition to time (e.g., statistical parameters of ambient light and sound) and frequency (e.g., number of detected activities) domain features, non-linear features generated from some specific data source (e.g., GPS radius of gyration and standard deviation of displacement) are extracted considering a time window of hours/days. Such features are then employed to train our machine learning models.

To ensure accurate detection of stress and depression, we will conduct comprehensive evaluations and comparisons of various machine learning models. Our analysis will encompass popular models such as XGBoost, CatBoost, SVM, random forest, and multilayer perceptron. By assessing the performance and capabilities of each model, we aim to identify the most suitable approach for effective detection of stress and depression.

2.2 Interaction Manager

The IM plays a crucial role as the intermediary among the data collection and analysis platform, chatGPT counselor, and the user, fulfilling multiple functions:

IM-Platform: The IM receives the user's mental status and contextual information from the platform. It also requests passive data from the platform asked by the user and/or chatGPT counselor over a defined time period.

IM-ChatGPT: The IM receives messages from the chatGPT counselor, including responses to user prompts as well as questions or requests directed towards the user or the platform. It forwards the user's mental status and contextual information, obtained from the platform, to the chatGPT counselor. Additionally, the IM relays user responses and questions to the chatGPT counselor.

IM-User: The IM initiates conversations on behalf of the user and may trigger counseling services based on the detection of the user's mental status and contextual information provided by the platform. It also communicates responses, questions, and suggestions generated by the chatGPT counselor and platform to the user. Furthermore, the IM presents information to the user about how stress and depression levels were calculated for promoting self-awareness and self-reflection.

Figure 2: Example of interaction between the IM and user when a) stress has been detected and b) the user requests particular data.

Figure 2 illustrates an example of the IM-user interaction. In Figure 2-a, the IM, supported by the chatGPT counselor, initiates a conversation when the user's stress level is detected by the platform. In Figure 2-b, the IM provides the user with the requested information regarding their daily activity chart. In short, the IM serves as the vital link connecting the platform, chatGPT counselor, and the user, facilitating information exchange, personalized interactions, and potentially triggering counseling services based on the user's mental state and context.

2.3 ChatGPT Counselor

The proposed chatGPT counselor is a customized model based on the standard chatGPT. The standard chatGPT is a transformer based model developed by OpenAI, which was trained on a vast amount of diverse internet text to generate responses and engage in conversations [12]. Although the standard chatGPT has a broad understanding of various topics and can generate creative and coherent responses, it lacks the knowledge of a specialized mental health specialist. To overcome such limitation, *WMGPT* customizes the standard chatGPT model through a fine-tuning process in which the pre-trained model is trained on specific mental-consultation datasets with carefully curated examples and feedback. The fine-tuning process tailors the chaGPT model's responses to the specific mental health domain, making it more accurate, reliable, and aligned with desired behavior as a specialized mental-health counselor. Inspired by the works in [15] and [13], we fine-tune the pre-trained ChatGPT model to obtain a specialized counselor by the following three steps:

(1) *Supervised fine-tuning:* The pretrained chatGPT model is trained using psychological counseling dataset, which contains conversations or dialogues between individuals seeking mental health support and qualified mental health professionals. The dataset will be mainly obtained from AI Hub, which is an integrated platform operated by the National

Information Society Agency of Korea. Currently, AI Hub contains more than 3000 cases and it will continuously increase through the collection of welfare call centers consultation data [6].

(2) *Creation of reward model:* The supervised fine-tuned model obtained in step one is now used to answer mental health related prompts. Four to nine answers will be provided by the model, which will then be ranked by mental health specialist. The answers provided by the fine-tuned model, together with their corresponding ranking scores, are then used to train a reward model.

(3) *Refinement via reinforcement learning:* The reward model obtained in step two is now exploited for refinement of the fine-tuned model via reinforcement learning. Specifically, we plan to use the early stopping policy approximation method [16]. By employing the reinforcement framework and reward model, the model is refined to generate higher-quality answers as judged by the mental health specialist.

Additionally, with appropriate prompt engineering [9], it is feasible to personalize the model to embody a desired persona, such as that of a specific mental health specialist. This further customization allows the model to adopt the characteristics and expertise of the chosen persona, enhancing its ability to provide tailored and specialized counseling services.

3 FUTURE WORK

Our future work involves developing *WMGPT* based on a thorough survey, consultation, and conducting a user study to evaluate the performance of the *WMGPT* in the wild.

Survey: We plan to conduct a literature review of existing online mental health consulting systems. By analyzing existing literature, we will explore the limitations that these systems currently face and examine the strategies that have been employed to overcome these challenges. The survey will help us identify gaps and provide possible directions to improve existing online mental health systems.

Consultation: We will seek input from mental health specialists regarding their perspective on online consultation system. Their insights and feedback will be invaluable in enhancing the online mental health system for the benefit of all users. By engaging with experts in the field, we aim to ensure that the system meets the highest standards of quality and effectiveness in providing mental health support.

User study: We will conduct a user study in the wild to evaluate the effectiveness of *WMGPT* counseling service. The study aims to address three primary research questions: 1) Does the counseling service aid in alleviating emotional stress and depression levels? 2) Does it improve self-awareness and self-reflection? 3) Does providing different types of explanations about how the user's mental state was assessed influence engagement and encourage seeking counseling? The explanations will be categorized into three types: no explanation, categorical explanation, and detailed explanation, providing varying levels of information on how *WMGPT* determines the user's mental state. This comprehensive evaluation will contribute to enhancing the system's effectiveness and user engagement.

ACKNOWLEDGMENTS

This research was supported in part by the National Research Foundation (NRF) under Grant NRF-2021M3A9E4080780 and in part by the NRF project under Grant NRF-2021R1I1A1A01041257.

REFERENCES

[1] Ana M. Bernardos, Marcos Pires, Daniel Ollé, and José R. Casar. 2019. Digital phenotyping as a tool for personalized mental healthcare. In *proceedings of the 13th EAI International Conference on pervasive computing technologies for healthcare*. 403–408.

[2] Alison Brunier. 2021. *WHO report highlights global shortfall in investment in mental health.* Retrieved May 24, 2023 from https://www.who.int/news/item/08-10-2021-who-report-highlights-global-shortfall-in-investment-in-mental-health

[3] Francisco Maria Calisto, João Fernandes, Margarida Morais, Carlos Santiago, João Maria Abrantes, Nuno Nunes, and Jacinto C Nascimento. 2023. Assertiveness-based Agent Communication for a Personalized Medicine on Medical Imaging Diagnosis. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–20.

[4] Jamie Danemayer, Cathy Holloway, Youngjun Cho, Nadia Berthouze, Aneesha Singh, William Bhot, Ollie Dixon, Marko Grobelnik, and John Shawe-Taylor. 2023. Seeking information about assistive technology: Exploring current practices, challenges, and the need for smarter systems. *International Journal of Human-Computer Studies* 177 (2023), 1–11.

[5] Saloni Dattani, Hannah Ritchie, and Max Roser. 2021. Mental Health. *Our World in Data* (2021). https://ourworldindata.org/mental-health.

[6] AI Hub. 2022. *Welfare call center consultation data.* Retrieved May 26, 2023 from https://www.aihub.or.kr/aihubdata/data/view.do?currMenu=115&topMenu=100&aihubDataSe=realm&dataSetSn=470

[7] Yonggeon Lee, Youngtae Noh, and Uichin Lee. 2023. Data Processing Pipeline of Short-Term Depression Detection with Large-Scale Dataset. In *2023 IEEE International Conference on Big Data and Smart Computing (BigComp)*. 391–392.

[8] Hao Liu, Huaming Peng, Xingyu Song, Chenzi Xu, and Meng Zhang. 2022. Using AI chatbots to provide self-help depression interventions for university students: a randomized trial of effectiveness. *Internet Interventions* 27 (2022), 1–8.

[9] Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. 2023. Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. *Comput. Surveys* 55, 9 (2023), 1–35.

[10] Sergazy Narynov, Zhandos Zhumanov, Aidana Gumar, Mariyam Khassanova, and Batyrkhan Omarov. 2021. Development of Chatbot Psychologist Applying Natural Language Understanding Techniques. In *2021 21st International Conference on Control, Automation and Systems (ICCAS)*. IEEE, 636–641.

[11] Kyo-Joong Oh, Dongkun Lee, Byungsoo Ko, and Ho-Jin Choi. 2017. A chatbot for psychiatric counseling in mental healthcare service based on emotional dialogue analysis and sentence generation. In *2017 18th IEEE international conference on mobile data management*. IEEE, 371–375.

[12] OpenAI. 2022. *Introducing chatGPT.* Retrieved May 26, 2023 from https://openai.com/blog/chatgpt

[13] Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. 2022. Training language models to follow instructions with human feedback. *Advances in Neural Information Processing Systems* 35 (2022), 27730–27744.

[14] Nicolas Rüsch, Alina Zlati, Georgia Black, and Graham Thornicroft. 2014. Does the stigma of mental illness contribute to suicidality? *The British Journal of Psychiatry* 205, 4 (2014), 257–259.

[15] Nisan Stiennon, Long Ouyang, Jeffrey Wu, Daniel Ziegler, Ryan Lowe, Chelsea Voss, Alec Radford, Dario Amodei, and Paul F Christiano. 2020. Learning to summarize with human feedback. *Advances in Neural Information Processing Systems* 33 (2020), 3008–3021.

[16] Mingfei Sun, Vitaly Kurin, Guoqing Liu, Sam Devlin, Tao Qin, Katja Hofmann, and Shimon Whiteson. 2022. You May Not Need Ratio Clipping in PPO. *arXiv preprint arXiv:2202.00079* (2022).

[17] Shuo Tian, Wenbo Yang, Jehane Michael Le Grange, Peng Wang, Wei Huang, and Zhewei Ye. 2019. Smart healthcare: making medical care more intelligent. *Global Health Journal* 3, 3 (2019), 62–65.

[18] Kobiljon Toshnazarov, Tae Hong Lee, and Youngtae Noh. 2023. WildStress: exploring rich situational contexts for stress detection in the wild. In *2023 IEEE International Conference on Big Data and Smart Computing (BigComp)*. 381–382.