Self-Help Psychological Intervention for Young Adults with COVID-19 in the Post-Pandemic Era –Developing a PST Chatbot Based on GPT-4

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Date: 2024-03-18T00:00:00+00:00

Abstract

To assist young individuals infected with COVID-19 in restoring and developing mental health equilibrium following the pandemic, we developed an online self-help psychological intervention robot that serves as a supplement to existing mental health resources. Initially, we employed prompt engineering techniques to construct a chatbot proficient in Problem-Solving Therapy (PST) based on the large language model GPT-4. Subsequently, we conducted a pilot test and a formal experiment to validate the chatbot' s effectiveness. Pilot test results demonstrated that the chatbot adhered to the core working procedures of PST during user interactions. Formal experiment results revealed that the PST chatbot outperformed the ordinary chatbot on the dimensions of problem identification and problem-solving, indicating that the PST chatbot can help users more rapidly locate issues troubling them and formulate feasible problem-solving plans. However, no significant difference was observed between the PST chatbot and the ordinary chatbot on the relationship quality dimension, nor were any differences in evaluations of the two chatbots identified with respect to gender and post-COVID sequelae. This suggests that the PST chatbot did not significantly improve human-robot relationship quality, yet the general acceptability and broad applicability of chatbots continue to offer certain advantages in practical applications. The research findings support the potential of large language models for innovatively implementing psychological self-help interventions.

Full Text

Preamble

Self-help Psychological Intervention for Young COVID-19-Infected Individuals in the Post-Pandemic Era: Developing a PST Chatbot

Based on GPT-4

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Abstract

To assist young people infected with COVID-19 in restoring and developing a balanced state of mental health after the pandemic, we developed an online self-help psychological intervention robot that can complement existing mental health resources. First, we utilized prompting engineering techniques to build a chatbot skilled in Problem-Solving Therapy (PST) based on the large language model GPT-4. Then, we conducted pre-testing and formal experiments to verify the effectiveness of the chatbot. The pre-testing results indicated that the chatbot followed the core work steps of PST during interactions with users. The formal experiment results showed that the PST chatbot performed better than the ordinary chatbot in terms of problem identification and problem-solving dimensions, indicating that the PST chatbot can help users quickly locate the problems that trouble them and develop feasible problem-solving plans. However, there was no difference between the PST chatbot and the ordinary chatbot in terms of relationship quality, and no differences were found in the evaluation of the two chatbots based on gender and post-COVID symptoms. This suggests that the PST chatbot did not significantly improve the quality of human-machine relationships, but the general acceptability and wide applicability of chatbots still have certain advantages in practical applications. The research results support the possibility of using large language models in innovative implementations of psychological self-help interventions.

Keywords: Self-help Psychological Intervention, GPT-4, Problem-Solving Therapy, Chatbot

1. Research Background

The multiple pressures and challenges brought about by the COVID-19 pandemic have significantly exacerbated psychological stress among young people, producing lasting impacts on their mental health. Many patients reported persistent mental health issues after recovery, including anxiety, depression, post-traumatic stress disorder, mood fluctuations, and cognitive decline (e.g., "brain fog") (Al-Aly, Xie, & Bowe, 2021; Lopez-Leon et al., 2021; Mazza et al., 2020). These mental health problems constitute important sources of suicide risk. Meanwhile, in the mental health field, social support is widely recognized as a protective factor against suicide risk. Research by Kleiman and Liu (2013) demonstrated that individuals who feel cared for and supported by others are more likely to seek help when facing crises. Thoits (2011) noted that strong social support networks can provide emotional support, information feedback, advice for coping with difficulties, and practical assistance, representing a viable means of reducing suicide risk. Therefore, to address the mental health support needs of young COVID-19-infected individuals in the post-pandemic era, and to help them restore and develop a balanced state of mental health during this critical life stage while reducing their suicide risk, we need to develop an easily accessible mental health support channel.

With the rapid development of digital technology, self-help psychological intervention tools, particularly chatbots, have emerged as an innovative form of social support. They provide a low-cost, easily accessible, and anonymous method to help populations who may be unable to obtain traditional therapy due to geographical constraints, social stigma, or limited financial resources (Vaidyam, Wisniewski, Halamka, Kashavan, & Torous, 2019). These AI-based chatbots can provide real-time feedback, support, and guidance through simulated conversations, offering users a non-judgmental environment where they can freely express their feelings and concerns (Fitzpatrick, Darcy, & Vierhile, 2017). Utilizing psychotherapy to construct chatbots for providing psychological interventions can serve as a useful supplement to mental health services (Fitzpatrick et al., 2017).

Problem-Solving Therapy (PST) is a psychological therapy that emphasizes reducing psychological stress and managing mental health problems by improving individuals' skills in solving daily life problems. The core assumption of PST is that the ability to cope with specific life problems is directly related to mental health status. By teaching effective problem-solving techniques, PST aims to enhance people' s self-efficacy and sense of control over life events, thereby helping them reduce and manage depression, anxiety, and other mental health issues (Malouff, Thorsteinsson, & Schutte, 2007; Nezu, Nezu, & D' Zurilla, 2012). The feasibility of developing PST-based chatbots has attracted researchers' attention. Such tools provide an interactive environment that guides users through PST steps, helping them identify problems, generate solutions, make decisions, and implement solutions. Since chatbots can provide support 24 hours a day, they are particularly suitable for delivering consistent, on-demand interventions without requiring the resource investment of traditional face-to-face therapy (Ly et al., 2014).

Through Large Language Models (LLM) and Prompt Engineering (PE), we can integrate Problem-Solving Therapy into chatbot programs to help individuals manage their own problems, thereby improving the accessibility and efficiency of mental health interventions. Large language models, such as GPT-3 or GPT-4, are deep learning-based AI models capable of understanding and generating human language. These models learn language complexity and how to answer questions, provide information, and write text by training on vast amounts of textual data. Prompt engineering is the process of designing and refining prompts to guide large language models to produce desired outputs.

In summary, the objective of this research is to utilize prompt engineering techniques to build a PST chatbot based on GPT-4, providing a self-help psychological intervention channel for young COVID-19-infected individuals to help them navigate the psychological turbulence in the post-pandemic period. GPT-4 possesses a powerful knowledge base and logical reasoning capabilities, and it is expected that the PST chatbot built with GPT-4 can provide emotional support, information feedback, and advice for coping with difficulties to young COVID-19-infected individuals, thereby enhancing their sense of efficacy in problem-solving and reducing suicide risk.

2.1. Building the PST Chatbot

Step 1: Designing the Prompt

Using prompt engineering techniques, we employed appropriate prompts to guide the large language model GPT-4 to generate outputs consistent with Problem-Solving Therapy. First, we created an initial prompt requiring the chatbot’ s dialogue logic to be based on the core principles and processes of PST. Then, we conducted iterative testing, using the designed prompts to interact with the model and observing whether the outputs aligned with expectations. Based on test results, we adjusted the prompt’ s structure, language, and details to improve the model’ s output until we obtained appropriate prompts. The specific process is shown in Figure 1 [Figure 1: see original paper].

(1) Initial Prompt Construction:

When constructing the initial prompt based on Problem-Solving Therapy, we designed the prompt to be detailed and comprehensive to guide GPT-4 in providing help centered on PST’ s core steps. The prompt instructed the chatbot to provide users with a clear PST framework and to establish a warm and supportive conversational environment. This approach encouraged open and honest dialogue, assisting users in achieving psychological improvement through a series of structured steps.

(2) Iterative Testing and Adjustment:

Iterative testing and adjustment are crucial steps in designing the chatbot. This process helps ensure that the chatbot’ s output not only adheres to the structure and principles of PST but can also actually help users. Using the initial prompt to interact with the model, we observed and evaluated whether the output followed PST’ s four steps. If the output did not meet expectations, we adjusted the prompt’ s content, structure, or wording until the chatbot could accurately conduct dialogues according to PST’ s process. The following are the specific steps for iterative testing and adjustment:

- **Iterative Testing:** Use the designed initial prompt to guide the large language model in generating appropriate response content. Initial interaction might be a simple user input such as: "I feel very anxious because I' m not sure if my career path is correct." Observe whether the model' s response can identify the user' s problem, provide goal-setting methods consistent with PST, guide users to explore possible solutions, and ultimately help users develop an action plan.
- **Evaluate Output:** Confirm whether the model' s output follows PST logic: first problem identification, then goal setting, followed by exploring solutions, and finally developing an action plan. Evaluate content quality, including whether suggestions are practical, respect user autonomy, and help users think about problems from different perspectives.
- **Output Adjustment:** If the model' s response fails to correctly follow PST steps or provides unrealistic solutions, adjust the prompt language. Adjustments may include improving directive wording to make it clearer (e.g., specifying what types of open-ended questions to use during problem identification) and increasing explicitness to ensure the model guides users through specific action steps rather than vague guidance.
- **Repeat Testing:** Use the adjusted prompt to retest, collect new output, and evaluate again. This process may require multiple iterations, with fine-tuning based on observed issues each time.
- **Documentation:** After each iteration, record which adjustments were effective and which were not. Documentation helps understand what types of prompts produce outputs closer to expectations and facilitates faster optimization of prompts for similar tasks in the future.
- **User Feedback Integration:** Integrate real user feedback into the iterative cycle to understand user needs and problems and expand dialogue adaptability and scope. User feedback can help determine whether prompts are actually easy for users to understand and whether the model' s responses meet users' actual needs and feelings.
- **Final Confirmation:** After multiple rounds of testing, adjustment, and evaluation, an optimized prompt is obtained. This prompt helps the chatbot efficiently assist users in processing and solving their problems according to PST methods.

The overall feedback and refinement process aims to create an empathetic chatbot that encourages user self-exploration and provides structured help. It not only reflects the PST framework but can also respond to users' specific psychological and emotional needs in a highly humanized manner.

Step 2: Building the Chatbot Website

We wrote a program using Gradio to build a website and called the ChatGPT API to initialize GPT-4 based on the trained prompts, generating an interactive chatbot website (code example shown in Figure 2 [Figure 2: see original paper]). The final PST chatbot operates according to the four core steps of Problem-Solving Therapy:

- **Problem Identification:** The chatbot needs to identify the user' s primary distress and challenges. It encourages users to directly express their concerns or problems to the chatbot, ensuring users feel understood and clarifying specific issues. For example: "What impact has this problem had on your life?"
- **Goal Setting:** Clear goal setting is crucial for successful problem solving. The chatbot can guide users to consider what their ideal outcome would be and help them break down this goal into smaller, more specific action items. For example: "What changes do you hope to see in your life or emotional state after solving this problem?"
- **Exploring Solutions:** Encourage users to think divergently and consider multiple possible solutions. The robot can provide guiding questions to facilitate thinking, such as: "What strategies can you think of that have helped you handle similar problems before?" Meanwhile, the robot can also provide suggestions and resources when necessary.
- **Developing a Plan:** At the implementation stage, the robot supports users in developing specific action steps. This can include determining timelines, resources, interpersonal support, and anticipating and planning for potential difficulties. For example: "Let' s identify what your first action step will be and when you will start."

2.2. Validating PST Chatbot Effectiveness

(1) Pre-testing

We recruited seven master' s students in counseling psychology who had received PST training to 试用和评价 (trial and evaluate) the PST chatbot. The pre-testing procedure was as follows:

- **Testing Preparation:** Ensure the chatbot' s stability and connectivity from a technical perspective to prevent technical failures during testing. Prepare clear testing guidelines, including testing procedures, scoring criteria, operation methods, and feedback methods.
- **User Guidance:** Before formal testing, introduce users to the PST chatbot' s functions, intended uses, and specific scoring requirements. Provide a testing protocol that clearly explains confidentiality guidelines, data usage rules, and user rights.
- **Conduct Testing:** Have users interact with the PST chatbot. The pretest webpage instructions are shown in Figure 3 [Figure 3: see original paper]. The experimenter provided immediate technical support when users encountered any problems. Users were encouraged to interact with the robot in the most natural way possible, as they would in real-life situations with humans.
- **Collect Feedback:** After testing, collect user feedback through questionnaires administered immediately after the conversation ended to ensure accuracy. Feedback content included:
  - **Degree of Conformity to PST Process** (Scoring criteria: 1-10

scale, where 1 indicates non-conformity to PST process and 10 indicates full conformity). This shows the extent to which the chatbot adheres to or deviates from the PST process.
  - **Helpfulness in Solving Distress** (Scoring criteria: 1-10 scale, where 1 indicates no help and 10 indicates extremely helpful). Raters were asked to provide how they used the solutions provided by the chatbot or how the conversation helped them think about problems.
  - **Specific Improvement Suggestions:** Invite users to provide specific improvement suggestions based on their professional knowledge and interactive experience. Collect suggestions regarding prompt construction, process guidance, response quality, etc.
  - **Complete Chat Duration:** Record the complete duration of user-chatbot interaction to judge user engagement and time efficiency of single sessions.
- **Data Analysis and Iterative Optimization:** Organize and analyze collected data using a combination of quantitative data (scores) and qualitative data (improvement suggestions) to measure effectiveness. Then develop optimization strategies based on feedback results, such as adjusting dialogue flow, enhancing response relevance, or improving the humanization level of chat logic. Make necessary technical improvements to the chatbot.

(2) Formal User Experiment

After optimizing the PST chatbot based on pre-test results, we conducted a formal online user experiment. A total of 100 young users who had been infected with COVID-19 were recruited for the experiment and randomly assigned to experimental and control groups, with an age range of 18-35 years. During the formal experiment, we ensured that except for using different chatbots, all other procedures were identical for both groups. The formal experiment chatbot webpage instructions are shown in Figure 4 [Figure 4: see original paper].

- **Experimental Group:** 50 participants (18 males, 32 females) experienced the trained PST chatbot. Typically after 4-8 rounds of interaction, the chatbot would provide a friendly closing message (e.g., "Today' s consultation ends here") along with some mental health hotlines, after which users could finish using the chatbot and complete the user experience questionnaire.
- **Control Group:** 50 participants (22 males, 28 females) experienced an untrained ordinary chatbot. After 4-8 rounds of interaction, users could finish using the chatbot and complete the user experience questionnaire.

The specific experimental procedure was as follows:

- **Design User Experience Questionnaire:** The experimenter compiled an initial questionnaire by reviewing literature and following questionnaire design procedures. Then a psychology professor specializing in suicide research provided improvement suggestions on the dimension classification and specific items of the initial questionnaire. The final revised user experience questionnaire included evaluations of three dimensions of the chatbot: problem cognition, problem solving, and relationship quality, with 17 items total (specific items shown in Table 1). (1) Problem cognition dimension (items 1-5) represents the degree to which the chatbot helps users gain clearer understanding of their current distressing problems. (2) Problem solving dimension (items 6-11) represents the degree to which users understand what methods should be used to solve their current distressing problems. (3) Relationship quality dimension (items 12-17) represents the level of relationship quality between users and the chatbot, where higher relationship quality indicates greater user willingness to communicate with the chatbot. A 10-point Likert scale was used, with "1" representing strongly disagree and "10" representing strongly agree.

- **Experiment Preparation:** Ensure the technical platform is stable and can support and run two different versions of chatbots: the optimized PST chatbot and the untrained ordinary chatbot.
- **User Recruitment and Assignment:** Recruit young people who had been infected with COVID-19, ensuring voluntary participation and awareness of research purposes and data types used. Use random assignment to ensure equal numbers in experimental and control groups with similar gender distribution ratios.
- **Standard Operating Instructions:** Introduce users to basic operations of the chatbot experiment and emphasize privacy and security guidelines. Ensure users understand the meaning of closing messages and inform them that they need to complete a user experience questionnaire after the experiment.
- **Data Analysis:** After the experiment, collect all completed questionnaire data from users and use independent samples t-tests to compare rating differences between groups to evaluate the effectiveness of the PST chatbot.

3.1. Pre-test Results

The rating results from seven graduate students in counseling psychology who received PST training are shown in Table 2 . The test results indicated that the PST chatbot generally conforms to the process design of Problem-Solving Therapy, can be helpful for people solving problem-related distress, and can utilize its powerful knowledge base to help users clarify their thoughts, find useful problem-solving methods, and develop action plans within a short time.

Specific improvement suggestions were organized in Table 3 . Some of these suggestions have been adopted to improve the PST chatbot, while others were not adopted due to technical reasons or other objective factors. Based on the improvement suggestions, the PST chatbot was updated to additionally provide available psychological intervention hotlines after completing its workflow, allowing users to call hotlines to seek professional help when needed.

Table 2. Pre-test Rating Results - Process Conformity Rating (out of 10): Mean score 8.43 - Effectiveness Rating (out of 10): Mean score 8.23 - Complete Chat Duration (minutes): Mean duration 9.14

Table 3. Specific Improvement Suggestions (Note: The table contains qualitative feedback from evaluators)

3.2. Formal User Experiment Results

Independent samples t-tests were used to analyze the data, with results shown in Table 4 . Results indicated that in the problem cognition dimension, the experimental group' s ratings were significantly higher than the control group' s ($t(88.31) = 3.14$, $p = 0.002$), suggesting that PST-based intervention can more effectively help users identify and understand the problems they face. Users were able to more accurately identify problems and gain clearer understanding of them through interaction with the PST chatbot, which is an important first step in problem solving.

In the problem solving dimension, the experimental group also significantly outperformed the control group ($t(98) = 3.34$, $p = 0.001$), indicating that the PST chatbot was more effective in guiding users to think about and select problem-solving strategies. Users were more inclined to use methods provided by the PST chatbot to cope with and solve problems, pointing to the potential value of PST chatbots in enhancing users' problem-solving skills.

However, in the relationship quality dimension, no significant difference was found between experimental and control groups ($t(91.23) = 1.07$, $p = 0.286$). This may mean that the quality of relationships users establish with PST chatbots and ordinary chatbots is roughly equivalent, or that the quality of human-computer interaction relationships did not improve due to the use of Problem-Solving Therapy. It may also be because users already have relatively high acceptance of chatbots, or because relationship quality is more influenced by other factors (such as chat interface friendliness, robot response speed, etc.).

As shown in Table 5 and Table 6 , no differences were found in evaluations of the two chatbots based on gender and post-COVID symptoms, indicating that chatbot effectiveness is universal across users of different genders and with or without post-COVID symptoms. This is particularly important for chatbot promotion, as it suggests that chatbots do not require excessive personalized adjustments for gender or infection status and have good generalizability.

Table 4. Comparison Results Between Experimental and Control Groups - Experimental group (n=50) - Control group (n=50)

Table 5. Gender Comparison Results - Male (n=40) - Female (n=60)

Table 6. Post-COVID Symptoms Comparison Results - With symptoms (n=31) - Without symptoms (n=69)

4. Discussion

This study compared PST chatbots and ordinary chatbots across three dimensions: problem cognition, problem solving, and relationship quality, finding that PST chatbots provided significant help to users in enhancing problem cognition and problem solving. This may be because the PST chatbot' s workflow conforms to the logical chain of problem solving, helping users discover the core of problems faster and propose more targeted suggestions to help users understand how to solve problems (Pandey & Sharma, 2023).

In the problem cognition dimension, the experimental group' s scores were significantly higher than the control group' s, suggesting that the PST chatbot helped users form clearer understanding of distressing problems through concrete and structured interventions. This effect may be consistent with Vlaescu et al.' s (2016) finding that technology-based mental health interventions can help users better understand treatment content and engage in self-management.

The significant difference between experimental and control groups in the problem solving dimension emphasizes the potential benefits of PST chatbots in providing problem solutions. This echoes Fitzpatrick et al.' s (2017) research, which noted that digital health interventions can effectively assist individuals in identifying problems and exploring possible solutions, which may consequently help improve overall mental health status.

However, no significant difference was found between experimental and control groups in the relationship quality dimension, indicating that users tend to communicate with PST chatbots and ordinary chatbots to a similar degree. This may be because relationship building functionality is limited in chatbots, a finding consistent with Miner et al.' s (2017) view that chatbot relationship building requires more humanized interaction design.

Additionally, gender and presence of post-COVID symptoms did not show significant differences in evaluating chatbot utility, suggesting the potential universality of chatbots. This aligns with Schueller et al.' s (2016) research, which found that technology-assisted psychological interventions do not require extensive personalized modifications for specific genders or health conditions. Nevertheless, more targeted PST programs could potentially be developed for individuals of different genders and health statuses to strengthen personalized intervention effects.

It should be noted that although PST chatbots were significantly superior to ordinary chatbots in specific psychological intervention dimensions, further research is needed to explore their long-term effects and application prospects in clinical settings. Future research could use larger sample sizes and longer-term randomized controlled trials to further test these preliminary findings.

This study examined the effects of PST chatbots compared to ordinary chatbots across multiple dimensions in a population of young people who experienced COVID-19 infection. The results support the application of PST chatbots in mental health interventions, particularly in helping users identify problems and explore solutions. Even though the PST chatbot did not significantly improve human-machine relationship quality, the general acceptability and wide applicability of chatbots still provide positive prospects for their further development and utilization in the mental health field. PST chatbots demonstrate the possibility of using AI technology to implement mental health self-help interventions and can serve as a complementary tool to existing mental health resources.

References

Al-Aly, Z., Xie, Y., & Bowe, B. (2021). High-dimensional characterization of post-acute sequelae of COVID-19. *Nature, 594*(7862), 259-264. doi:10.1038/s41586-021-03553-9

Fitzpatrick, K. K., Darcy, A., & Vierhile, M. (2017). Delivering Cognitive Behavior Therapy to Young Adults With Symptoms of Depression and Anxiety Using a Fully Automated Conversational Agent (Woebot): A Randomized Controlled Trial. *JMIR Mental Health, 4*(2), e19. doi:10.2196/mental.7785

Kleiman, E. M., & Liu, R. T. (2013). Social support as a protective factor in suicide: Findings from two nationally representative samples. *Journal of Affective Disorders, 150*(2), 540-545. doi:https://doi.org/10.1016/j.jad.2013.01.033

Lopez-Leon, S., Wegman-Ostrosky, T., Perelman, C., Sepulveda, R., Rebolledo, P. A., Cuapio, A., & Villapol, S. (2021). More than 50 long-term effects of COVID-19: a systematic review and meta-analysis. *Scientific Reports, 11*(1), 16144. doi:10.1038/s41598-021-95565-8

Ly, K. H., Trüschel, A., Jarl, L., Magnusson, S., Windahl, T., Johansson, R., . . . Andersson, G. J. B. O. (2014). Behavioural activation versus mindfulness-based guided self-help treatment administered through a smartphone application: a randomised controlled trial. *BMJ Open, 4*.

Malouff, J. M., Thorsteinsson, E. B., & Schutte, N. S. (2007). The efficacy of problem solving therapy in reducing mental and physical health problems: a meta-analysis. *Clinical Psychology Review, 27*(1), 46-57. doi:10.1016/j.cpr.2005.12.005

Mazza, M. G., De Lorenzo, R., Conte, C., Poletti, S., Vai, B., Bollettini, I., . . . Benedetti, F. (2020). Anxiety and depression in COVID-19 survivors: Role of inflammatory and clinical predictors. *Brain, Behavior, and Immunity*. doi:https://doi.org/10.1016/j.bbi.2020.07.037

Miner, A. S., Milstein, A., & Hancock, J. T. (2017). Talking to Machines About Personal Mental Health Problems. *JAMA, 318*(13), 1217-1218. doi:10.1001/jama.2017.14151

Nezu, A., Nezu, C., & D' Zurilla, T. (2012). *Problem-Solving Therapy: A Treatment Manual*.

Pandey, S., & Sharma, S. (2023). A comparative study of retrieval-based and generative-based chatbots using Deep Learning and Machine Learning. *Healthcare Analytics, 3*, 100198. doi:https://doi.org/10.1016/j.health.2023.100198

Schueller, S. M., Washburn, J. J., & Price, M. (2016). Exploring Mental Health Providers' Interest in Using Web and Mobile-Based Tools in their Practices. *Internet Interventions, 4*(2), 145-151. doi:10.1016/j.invent.2016.06.004

Thoits, P. A. (2011). Mechanisms linking social ties and support to physical and mental health. *Journal of Health and Social Behavior, 52*(2), 145-161. doi:10.1177/0022146510395592

Vaidyam, A. N., Wisniewski, H., Halamka, J. D., Kashavan, M. S., & Torous, J. B. (2019). Chatbots and Conversational Agents in Mental Health: A Review of the Psychiatric Landscape. *Canadian Journal of Psychiatry, 64*(7), 456-464. doi:10.1177/0706743719828977

Vlaescu, G., Alasjö, A., Miloff, A., Carlbring, P., & Andersson, G. (2016). Features and functionality of the Iterapi platform for internet-based psychological treatment. *Internet Interventions, 6*, 107-114. doi:10.1016/j.invent.2016.09.006

Author Contributions Statement

Liuling Mo, Tingshao Zhu, He Li: Conceived research ideas and designed research protocols;
Liuling Mo, Yanbo Zhang: Conducted experiments;
Liuling Mo, Peixin Cun: Collected, cleaned, and analyzed data;
Liuling Mo: Drafted manuscript;
Liuling Mo: Revised final version of manuscript.

Note: Figure translations are in progress. See original paper for figures.

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