Parallel Psychological Crisis Intervention: Method Construction and Implementation Conception

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Abstract

心理危机干预面临动态监测、精准预测与策略优化的方法挑战，传统方法难以应对心理状态的复杂性和个性化需求。本文探讨把平行智能理论引入心理危机干预，提出一个平行心理危机干预框架的概念。该框架基于 ACP 方法 (Artificial society, Computational experiments, Parallel execution，人工系统 ＋ 计算实验 ＋ 平行执行)，试图通过构建人工心理系统实现状态建模，通过计算实验实现心理状态推演与干预策略评估，通过平行执行实现虚实交互的策略优化，旨在为实现可计算、可实验、可迭代的心理危机干预方法提供初步框架。作为该框架的概念验证原型，本文设计了大语言模型驱动的多智能体系统 PsyRescueGPT。该系统构建了覆盖“监测分析与预测—策略生成与评估—平行执行与优化”的全流程，旨在为心理危机干预从经验驱动转向计算驱动探索一条可行的技术路径。

Full Text

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Abstract Psychological crisis intervention faces methodological challenges in dynamic monitoring, precise prediction, and strategy optimization, while traditional methods have difficulty coping with the complexity of psychological states and the need for personalization. This paper explores the introduction of parallel intelligence theory into psychological crisis intervention and proposes the concept of a framework for parallel psychological crisis intervention. Based on the ACP approach (Artificial society, Computational experiments, Parallel execution; artificial systems + computational experiments + parallel execution), the framework seeks to realize state modeling by constructing artificial psychological systems, to realize the evolution of psychological states and the evaluation of intervention strategies through computational experiments, and to realize strategy optimization with virtual-real interaction through parallel execution, with the aim of providing a preliminary framework for developing computable, experimentally testable, and iteratively improvable methods for psychological crisis intervention. As a proof-of-concept prototype of this framework, this paper designs **PsyRescueGPT**, a large-language-model-driven multi-agent system. The system constructs a full process covering "monitoring analysis and prediction–strategy generation and evaluation–parallel execution and optimization," aiming to explore a feasible technical pathway for shifting psychological crisis intervention from experience-driven to computation-driven.

[**Keywords**] psychological crisis intervention; parallel intelligence; ACP; large language model; multi-agent system; personalized intervention

[**Classification No.**] B841.4

Parallel psychological crisis intervention: framework and conceptions

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[**Keywords**] psychological crisis intervention, parallel intelligence, ACP, Large Language Models, multi-agent systems, personalized intervention

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computation-driven practice.

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1 Introduction

A psychological crisis refers to an emergency state in which, when facing a sudden event or difficult situation, an individual is unable to resolve the problem through conventional coping mechanisms, leading to a disruption of psychological equilibrium (Caplan, 1964). According to 2023 data from the World Health Organization, approximately 700,000 people worldwide die by suicide each year (World Health Organization, 2023), and about 80% of these cases show identifiable warning signs (Washington State Department of Health, 2018). This highlights the urgent need for dynamic monitoring and precise intervention in psychological crises. Psychological crisis intervention aims to help individuals restore psychological equilibrium and prevent adverse events through rapid risk assessment and personalized support (Lindemann, 1944). However, at the methodological level, this field faces fundamental challenges: psychological states are highly dynamic, complex, and individually heterogeneous. As a result, traditional intervention methods that rely heavily on static scales [such as the BDI (Beck Depression Inventory), Beck et al., 1961; and the PHQ-9 (Patient Health Questionnaire-9), Kroenke et al., 2001] and post-event interviews have difficulty achieving real-time crisis monitoring, precise risk prediction, and dynamic optimization of intervention strategies (Torous & Walker, 2019).

In recent years, intelligent technologies such as machine learning and Large Language Models (LLMs) have brought new tools to psychological crisis intervention, focusing mainly on digital-twin-based psychological modeling (Katsoulakis et al., 2024; Shen et al., 2024; Tan & Wei, 2025), psychological state assessment (Brickman et al., 2025; Sprint et al., 2024; Kjell et al., 2024), crisis prediction and identification (Garriga et al., 2022; Lee et al., 2024; Xu et al., 2024), generation of personalized intervention strategies (Stade et al., 2024; Ferrario et al., 2024), and generative intervention scenarios (Sezgin & McKay, 2024; Hua et al., 2025). However, these studies are often "fragmented" and lack a full-process approach that, from a systems-methodology perspective, covers monitoring, evaluation, inference, execution, and optimization.

process-oriented research framework (Guo et al., 2024). Existing LLM-driven systems still have shortcomings in areas such as multimodal data fusion, human–machine collaborative decision-making, and computable experiments for intervention strategies.

Psychological crises arise from complex interactions among individual, family, and social factors, constituting a typical complex system (James & Gilliland, 2025). Parallel intelligence theory, centered on the ACP approach—artificial systems: Artificial society; computational experiments: Computational experiments; parallel execution: Parallel execution—provides methodological support for the management of complex systems (Wang Feiyue, 2004a, 2004b, 2006), and has been applied in fields such as transportation, manufacturing, and agriculture (Yang Jing et al., 2023). However, there remains a relative lack of research that deeply integrates ACP with LLMs and multi-agent technologies in the mental health domain so as to systematically address the challenges of psychological crisis intervention. On the one hand, existing LLM research in mental health has mostly focused on single functional modules such as assessment, prediction, or dialogue generation, lacking a unified methodological framework that integrates these capabilities into a computable, experimentally testable, and iterative research process. On the other hand, existing ACP research has not yet explored methodological construction or technical implementation for the psychological system—a complex system that is subjective, dynamic, and strongly socially embedded.

Therefore, based on parallel intelligence theory, this paper proposes a framework for parallel psychological crisis intervention. With the ACP approach as its underlying paradigm, the framework integrates the cognitive understanding capabilities of LLMs with the collaborative execution capabilities of multi-agent systems, aiming to construct a research methodology that covers the construction of artificial psychological systems, computational experimental deduction, and optimization through parallel execution. By constructing artificial psychological systems, this approach enables computable modeling of individual psychological states; by using computational experiments, it enables the safe deduction and quantitative evaluation of intervention strategies; and through parallel execution, it realizes closed-loop interaction and dynamic optimization between virtual strategies and real-world interventions. This framework seeks to address the dynamic, complex, and personalized challenges of psychological crises, exploring a paradigm shift from experience-driven to computation-driven approaches and from static response to dynamic foresight, while providing a "computable, experimentally testable, and optimizable" research methodology for psychological crisis intervention.

2 Related Work on Psychological Crisis Intervention

2.1 Applications of LLMs in Psychological Crisis Intervention

From a methodological perspective, this section reviews the current applications of LLMs across various stages of psychological crisis intervention, including psychological digital twins, psychological state assessment, psychological crisis prediction, and intervention strategy generation.

(1) Psychological digital twin modeling

Mental health digital twins (MHDTs) refer to the use of individuals' multimodal data—such as physiological data, behavioral data, social interactions, subjective reports, and electronic medical records—in information space

a dynamic, computable, and highly personalized virtual model constructed within it. Through data-driven and mechanistic models, this model can simulate, map, predict, and understand individuals' psychological states, processes, and behaviors in the real world, thereby providing a computational object for the simulation-based testing of intervention strategies (Spitzer et al., 2023). Kokkas et al. (2025) developed a generative-AI-driven twin model for older adults to provide personalized intervention recommendations. However, existing modeling methods remain immature in such respects as the representation of psychodynamics, the handling of missing data, and ethical constraints (Vildjiounaite et al., 2023), which limits their reliability and generalizability as an experimental basis. Recent practice suggests that constructing artificial systems capable of faithfully reflecting the dynamic changes of psychological states still requires addressing key methodological issues such as multisource data fusion and model-validity verification.

(2) Psychological State Assessment

By parsing the semantic, syntactic, and affective nuances of natural language, LLMs offer the potential to bring a paradigm shift to psychological state assessment. Unlike traditional scales, which rely on discrete and retrospective self-reports, LLMs can conduct continuous, dynamic, and systematic analyses of social media posts, transcripts of clinical interviews, and even conversation records (Pellert et al., 2024). This capability enables them to capture dynamic fluctuations in psychological states that are difficult for traditional methods to reach—for example, identifying early signals of depressive states through subtle changes in linguistic style (Bunt et al., 2025)—thereby making real-time, low-burden psychological assessment possible.

However, this data-driven approach introduces challenges. First, assessment bias is a prominent issue. The training data of LLMs themselves may contain sociocultural biases, leading to differential and potentially inaccurate assessments of the psychological states of groups that differ by gender, ethnicity, or socioeconomic status (Lawrence et al., 2024). Second, interpretability is poor. Although LLMs can output a risk score, they cannot provide a clear decision pathway in the way a physician can, which hinders their clinical application. Finally, a model trained in one cultural context may be unable to accurately understand modes of emotional expression or somatic symptoms of psychological distress in another culture; its reliability and validity therefore require cross-cultural validation.

To address these challenges, technologies such as Adaptive RAG (adaptive retrieval-augmented generation, Adaptive Retrieval-Augmented Generation) have been applied to large language models, enabling them to complete assessments using standardized psychological questionnaires in a zero-shot manner by analyzing users' social media posts and to predict the corresponding scores (Ravenda, et al., 2025). This approach not only enables the transformation of unstructured personal texts into structured assessments; by retrieving information from reliable knowledge sources to strengthen the grounding of the generation process, it also improves the interpretability and standardization of assessment results. Future research needs not only to continue improving the technical accuracy of models, but also to design effective human–AI collaboration mechanisms to ensure the accuracy, fairness, and clinical practicality.

(3) Psychological Crisis Prediction

Research on psychological crisis prediction has achieved an important transition from single data sources to multimodal data integration. By integrating information such as electronic health records, wearable-device data, and natural language, machine-learning models have significantly improved the timeliness of risk identification. Studies show that, by analyzing features such as language patterns, frequency of social activity, and heart-rate variability, models can identify an upward trend in suicide risk several days before traditional assessment (Garriga et al., 2022).

However, most models stop at outputting risk probabilities; they cannot explain the causes of risk and have not formed a causal closed loop with the intervention stage (Roy et al., 2020), making it difficult to translate prediction results into executable personalized intervention plans. Precision psychiatry indicates the need to move beyond simple predictive models and to develop models capable of distinguishing causal mechanisms (Seyedsalehi et al., 2025). By constructing "counterfactual" prediction models, causal machine learning can not only predict relevant states but also evaluate the individualized effects of intervention measures, thereby providing evidence for personalized treatment selection. At the practical level, although tiered early-warning mechanisms have significantly shortened the cycle of risk identification (Mansoor & Ansari, 2024; Hill et al., 2025), how to transform prediction scores into effective interventions remains a challenge.

(4) Intervention Strategy Generation and Personalized Implementation

LLMs can generate dialogue scripts and personalized intervention plans (Torous & Blease, 2024; Stade et al., 2024), and can implement them through technologies such as chatbots (Heinz et al., 2025; Danieli et al., 2022) and generative scenarios (Zeiler et al., 2025; Martinez et al., 2021). Studies show that LLM-based chatbots can provide standardized responses in suicide-crisis interventions, while social robots can also help autistic patients practice social skills. However, most such research remains at the stage of strategy generation or outcome reporting, lacking systematic methodological designs for first placing strategies in virtual environments to conduct preliminary effect demonstrations (Nahum-Shani et al., 2016), as well as for carrying out continuous optimization and closed-loop feedback in real environments.

Although existing studies have explored the role of multi-agent systems in integrating the above links (Zhang et al., 2024; Bi et al., 2025; Kalton et al., 2016), their system architectures tend to emphasize functional coordination and have not yet formed frameworks and methods centered on "artificial systems–computational experiments–parallel execution" that support continuous iteration and verification. Current research shows evident methodological gaps in areas such as cross-modal data fusion, human-in-the-loop collaborative decision-making mechanisms, and closed-loop validation of the full intervention process, which constrains the advancement of intelligent intervention from tool innovation to the improvement of research methodology.

In summary, whether traditional intervention methods that rely on clinical interviews, psychological scales, and expert experience, or digital intervention systems based on LLMs, all still face challenges in advancing psychological-crisis intervention toward a set of research methods that are computable, experimentable, and iteratively improvable. First, intervention targets lack computable system-level representations. Traditional methods rely on subjective narratives and discrete scale scores; digital methods, although capable of processing continuous text or multimodal data, are mostly used for immediate response and have not yet organized such data into dynamically evolving, operationally computable artificial psychological systems. As a result, psychological states are difficult to turn into system objects that can be computed and deduced. Second, intervention strategies lack a safe, systematic experimental environment. Whether clinical decision-making or automated strategies based on LLMs are concerned, evaluations of their effects mostly depend on real-world implementation or offline data analysis. Constrained by ethics and practical risks, high-frequency, multi-scenario, and controllable computational experiments and verification have not yet been conducted before intervention; strategy optimization therefore often lags behind and depends on experience. Third, the intervention process lacks a closed-loop iterative mechanism that links the virtual and the real. The above methods mostly follow linear processes such as "assessment, intervention, follow-up" or "perception, generation, response." Even if digital systems can achieve partial automation, their model updating and strategy adjustment are often disconnected from the actual intervention process, and a closed loop of continuous feedback, real-time calibration, and parallel optimization has not yet been established. Therefore, existing paradigms have not yet transformed psychological-crisis intervention into a computable, experimentable, and iteratively improvable scientific problem; new research frameworks and methods need to be explored.

2.2 Parallel Intelligence and Related Application Work

(1) Theoretical Framework of Parallel Intelligence

Parallel intelligence theory is an interdisciplinary theory based on ACP, providing methodological support for solving management and control problems in complex systems (Wang Feiyue et al., 2004a, 2004b, 2006). As shown in Figure 1, its core components include artificial systems, computational experiments, and parallel execution. Artificial systems refer to the construction of digital twins similar to real systems, used to simulate actual systems; computational experiments refer to experiments conducted within artificial systems to explore possible management-and-control schemes and optimal strategies; parallel execution refers to executing experimental results in parallel with real systems to achieve dynamic optimization. Through the construction of artificial systems, the iteration of computational experiments, and interaction between virtual and

Figure 1. Theoretical framework of parallel intelligence. The diagram shows an "Artificial System (A)" and an "Actual System" linked by "Parallel Execution (P)," with "Computational Experiments (C)" connecting three intelligence modules: "Learning and Training / Descriptive Intelligence," "Experimentation and Evaluation / Predictive Intelligence," and "Management and Control / Prescriptive Intelligence."

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real systems, parallel intelligence theory compensates for the shortcomings of traditional methods in dealing with complex, dynamic, and uncertain systems.

The ACP method can build the "virtual" and "soft" parts of complex and intelligent systems, fully using quantitative and real-time computation to solve practical problems in complex systems. An artificial system is a generalized knowledge model and may be regarded as an extension of traditional mathematical modeling or analytical modeling; computational experimentation is a pathway for analyzing, predicting, and selecting complex decisions, and represents an advancement of simulation; parallel execution is a new type of closed-loop optimization and collaborative control mechanism formed by virtual–real interaction, thereby guiding action and locking onto objectives. Closed-loop feedback, virtual–real interaction, and parallel execution between artificial systems and actual systems can realize effective management and control of complex systems, thereby generating an integrated set of descriptive intelligence, predictive

parallel intelligence that integrates descriptive intelligence, predictive intelligence, and prescriptive intelligence, thereby enabling the description, prediction, and management and control of real systems (Fei-Yue Wang et al., 2016). At present, parallel intelligence has been widely applied in industries such as transportation, manufacturing, medicine, military affairs, and social governance. It has also been extensively applied and has achieved substantial development in research domains such as parallel control and intelligent control, parallel robotics and parallel manufacturing, parallel management and intelligent transportation, parallel medicine and smart health, parallel ecology and parallel society, parallel economic systems and social computing, parallel military systems, parallel cognition and parallel philosophy (Jing Yang et al., 2023).

Figure 1. Theoretical framework of parallel intelligence

(2) Analysis of the applicability of parallel intelligence to psychological crisis intervention

According to the cyber-physical-social system (CPSS, Cyber-Physical-Social Systems) framework (Wang, 2010), the human psychological system also constitutes a CPSS. It is a product formed through the joint action of biological entities in physical space, information media in information space, and social networks in social space; that is, biological entities are embedded into social networks through the empowerment of information media, forming a complex system with the triple attributes of physicality, sociality, and informationality. Specifically, physicality is manifested in biological entities in physical space as the material basis and is constrained by neurophysiological laws; sociality is manifested in the dynamic evolution that depends on interpersonal interaction, cultural contexts, and networks of social relations; and informationality is reflected in the realization of cognitive processes through information flow and in deep coupling with digital space, especially in the current digital era. Based on this framework, psychological crises are disorders of coordination among the physical, social, and informational dimensions—for example, genetic susceptibility, social isolation, and interaction with negative information flows may induce depression. It is therefore necessary to integrate multisource heterogeneous data, dynamically monitor physical signs, social behaviors, and information exposure, and implement coordinated intervention across the physical, social, and information layers: at the physical layer, pharmacological interventions regulate neural transmission; at the social layer, family therapy reconstructs support; and at the information layer, algorithms purify the cognitive environment.

The theory of parallel intelligence was born in response to the complexity of managing CPSSs (Wang, 2010). Its core ACP method can address the limitations of existing psychological crisis intervention by mapping physical space and social space into information space, in

optimal intervention plan through computational deduction in a virtual environment, and ultimately collaboratively regulate the ternary physical–social–information space. Its implementation is divided into three stages. In the artificial-system stage, the system integrates multisource data such as physical signals, social signals, and information trajectories, and constructs an artificial psychological system in the information space to simulate the dynamic evolution of the real psychological system, thereby enabling proactive prediction of psychological-crisis risk. In the computational-experiment stage, on the basis of the artificial psychological system and in combination with individual states and behavioral patterns, personalized intervention strategies and gamified deduction scenarios are generated, and the optimal plan is selected through computational experiments. In the parallel-execution stage, with the aid of reinforcement learning and human–machine integration technologies, the selected strategy is applied to the real system, and closed-loop optimization of the strategy is carried out on the basis of multisource dynamic monitoring data, so as to maximize intervention effectiveness.

This paper adopts the CPSS framework not to simplify human psychology into purely physical or informational processes, but rather to systematically describe and model, at the methodological level, the complexity of psychological crises. The psychological system itself has a biological basis, social embeddedness, and characteristics of information processing. As an analytical framework, CPSS helps integrate multisource heterogeneous data—such as physiological signals, social interactions, and cognitive expressions—thereby enabling a comprehensive understanding of the formation and evolution of psychological crises. What this paper proposes is a computational-method framework: under the premise of respecting the subjectivity, dynamism, and integrity of psychological phenomena, computational means are used to enhance our capacity to identify, predict, and intervene in psychological crises. In essence, this framework is a "modeling language," rather than a reductionist explanation of the nature of psychology.

3 Parallel Psychological-Crisis Intervention Framework and Methods

Based on the ACP method in parallel intelligence theory (Wang Feiyue et al., 2004a, 2004b, 2006), this section proposes and elaborates in detail a parallel psychological-crisis intervention framework, as shown in Figure 2. The framework aims to transform traditional passive responses into advance prediction and active prevention by constructing an artificial psychological system that interacts in parallel with the real psychological system, thereby realizing dynamic modeling, experimental evaluation, and systematic intervention for psychological crises.

Figure 2. Parallel psychological-crisis intervention framework

Top spaces: **Social space**; **Physical space**; **Information space**
Parallel systems: **Artificial psychological system** **Real psychological system**
Parallel execution: **virtual-real synchronization and interactive optimization**
Computational experiment: **crisis prediction and strategy evaluation**
Intelligent modules: **Learning and training—descriptive intelligence**; **Experimentation and evaluation—predictive intelligence**; **Management and control—guidance intelligence**

3.1 Artificial Psychological System: Digital Modeling of Individual Psychology

The artificial system refers to a virtual system constructed by computer, corresponding to the actual system and capable of interacting with it (Wang Feiyue et al., 2004b, 2006). An artificial psychological system is an individualized digital-twin model constructed specifically for the field of psychological crisis intervention. The construction of an artificial psychological system comprises an initial construction stage and a dynamic evolution stage. The initial construction stage aims to establish an individual' s basic psychological model. The system first performs multimodal data fusion, integrating multisource historical data about the individual, including physiological signals recorded by wearable devices, behavioral trajectories collected by smart terminals, contextual data obtained by environmental sensors, and subjective reports deeply parsed by large language models. After feature extraction and standardized processing, these data are analyzed for cross-modal associations through a pretrained large-model architecture, mining the potential mapping relationships among physiology, behavior, context, and subjective experience. On this basis, the system injects domain knowledge from psychology—such as developmental patterns of psychopathology and crisis-intervention decision-making—to form a foundational psychological representation model with domain adaptability. The dynamic evolution stage realizes the continuous optimization of the individual' s foundational model. Once the foundational model has been established, the system continuously updates the model through real-time data streams and intervention-feedback data, using a parameter self-calibration mechanism. Thus, a structured model consistent with psychological theory is established through initial construction, while the model' s sensitivity and adaptability to the individual' s trajectory of change are maintained through dynamic evolution, supporting subsequent crisis prediction, strategy generation, and effect evaluation.

3.2 Computational Experiments: Crisis Prediction and Strategy Evaluation

Computational experiments use the artificial system as a "computational laboratory," employing large-scale, controllable simulations to analyze and evaluate the various possible behaviors of the system under different contexts, thereby providing support for real-world decision-making (Wang Feiyue et al., 2004b, 2006). Within the framework of parallel psychological crisis intervention, computational experiments include crisis prediction, strategy generation, and strategy evaluation. Crisis prediction refers to predicting, on the basis of the artificial psychological system and by running predictive models, the probability of occurrence of specific crisis events, such as suicide risk within the next 24 hours. Strategy generation refers to producing intervention strategies consistent with evidence-based practice, based on the predicted risk type, severity, and individual characteristics, using a strategy-generation model. Strategy evaluation and optimization refer to taking different intervention strategies as input variables, simulating their implementation in the artificial psychological system, and observing and quantifying their effects on the system state. By comprehensively evaluating the virtual risk–benefit ratio of each strategy, the optimal plan can then be selected.

3.3 Parallel Execution: Closed-Loop Optimization Through Virtual-Real Interaction

Parallel execution is the bridge connecting the virtual world and the real world. Through the parallel operation and continuous interaction of the artificial system and the actual system, it forms an intelligent system characterized by virtual–real interaction, closed-loop feedback, and collaborative evolution (Wang Feiyue et al., 2004b, 2006). In this process, the actual system provides real operational data to the artificial system, while the artificial system feeds back analysis, prediction, and decision recommendations to the actual system through computational experiments, so as to

guiding it to evolve toward a more optimal state. Within the framework of this paper, parallel execution is embodied in the synchronized implementation of strategies across the virtual and the real, together with continuous closed-loop optimization. After computational experiments identify the optimal intervention strategy in the artificial system, that strategy is executed synchronously in both the real world and the artificial psychological system. Feedback data generated by real-world interventions continuously flow back into the artificial psychological system—such as users' physiological indicators and behavioral responses—and are used to dynamically calibrate the parameters of the artificial psychological system. For example, after the system captures a user' s positive galvanic skin response during a real-world intervention, it is used to optimize the mapping relationship for "positive intervention response" in the artificial psychological model; conversely, if an intervention proves ineffective, the system automatically triggers alternative plans that were rehearsed in the computational experiments.

In sum, ACP provides a structured and computable research pathway for psychological crisis intervention, with its capabilities reflected in three respects. First is the mapping capability of the artificial psychological system. It maps dynamically changing psychological states into operable and computable objects, addressing the challenge that intervention targets are difficult to render computational. Second is the inferential capability of computational experiments. In a safe and controllable virtual environment, it supports high-frequency, multi-scenario simulation, deduction, and effectiveness evaluation of intervention strategies, addressing the challenge that strategies cannot be safely tested through trial and error. Finally, there is the iterative capability of parallel execution. Through continuous interaction and feedback between virtual and real systems, it applies selected strategies to real-world interventions and forms a self-optimizing closed loop, addressing the challenge that the intervention process is difficult to dynamically fine-tune. In summary, "computable, experimentable, and iterable" are not only a set of capabilities that ACP brings to psychological crisis intervention, but also the foundation of its methodology.

4 Concept Validation Prototype: PsyRescueGPT Multi-Agent System

PsyRescueGPT is the concept validation prototype proposed in this paper. It aims to realize the methodological conception of the parallel psychological crisis intervention framework through a multi-agent architecture driven by large language models. Its design goal is to construct a method-validation process—from data perception, predictive analysis, strategy generation, and experimental evaluation to decision execution—through a multi-agent system driven by human-machine collaboration. The system architecture and workflow below are both methodological and technical conceptions based on the feasibility of existing technologies.

4.1 System Architecture

As shown in Figure 3, PsyRescueGPT adopts an LLM-driven multi-agent architecture, including a dynamically evolving artificial psychological system and five agents.

Artificial psychological system: This is the digital foundation of the entire framework, constructed and optimized through a multi-stage process. In the initial stage, based on users'historical data and domain knowledge, retrieval-augmented generation technology (Lewis, et al., 2020) is used to construct the initial psychological state model. In the operational stage, the system periodically achieves dynamic optimization through a continual-learning mechanism. The real-time multimodal data provided by the perception agent are encoded into unified representations, including physiological signals,

behavioral patterns, linguistic expression, and so forth. Through techniques such as parameter-efficient fine-tuning (Hu, et al., 2021), the model parameters are continuously calibrated to ensure that they always reflect the user' s most recent psychological state, thereby providing a reliable artificial psychological system for subsequent computational experiments.

Perception agent: It serves as the system' s "multimodal data fusion center," responsible for integrating heterogeneous data from wearable devices, mobile terminals, and environmental sensors. This agent uses specialized encoding networks to transform raw data into standardized feature vectors—for example, temporal convolutional networks for processing physiological signals (Bai et al., 2018) and Transformers for processing textual data (Vaswani et al., 2017). It also establishes semantic associations among different data sources through a cross-modal attention mechanism, providing high-quality data input for the dynamic updating of the artificial psychological system.

Prediction agent: As a "risk early-warning and analysis engine," it carries out psychological crisis prediction based on the updated artificial psychological system. This agent may adopt technologies such as graph neural networks (Fan, et al., 2021) to model the evolution of the user' s state in the artificial psychological system as a dynamic graph structure. By analyzing transition patterns among state nodes, it enables quantitative prediction of the probability of psychological crisis over the next 24–72 hours, and identifies key risk factors and their interaction mechanisms, thereby providing precise targets for the formulation of intervention strategies.

Figure contents

- **Multimodal Data**

- Physiological data
- Behavioral data
- Situational data
- Psychological data

- **Various Models**
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  - Psychological digital twin
  - Human digital twin
  - Evaluation model
- **PsyRescueGPT**
  - Monitoring agent
  - Prediction agent
  - Strategy agent
  - Experiment agent
  - Decision agent
  - Artificial psychological system
- **User Groups**
  - Doctors
  - Friends
  - Communication interface
  - Family
  - Individual
- **Various Models**
  - Strategy generation model
  - Experimental planning model
  - Strategy deduction model
  - Scenario generation model
  - Strategy library
  - Knowledge library
  - Scenario library

Figure 3. PsyRescueGPT: Conceptual prototype for parallel psychological crisis intervention

Strategy agent: It assumes the role of an "intervention-plan designer,"generating structured intervention strategies based on the analysis results of the prediction agent. The work of this agent is based on Storyline-based large-model prompt generation

engineering (Brown et al., 2020; Wei et al., 2022). Through a carefully designed series of prompts, the large model is guided to generate personalized intervention plans—comprising such elements as dialogue scripts, scenario settings, and behavioral tasks—based on the user' s specific situation, risk causes, and psychological theories, while ensuring that the plan conforms to evidence-based practice and ethical norms.

Experimental agent: Serving as a "virtual intervention laboratory," it is responsible for verifying the effectiveness of strategies within the artificial psychological system. This agent takes the series of prompts generated by the strategy agent as stimulus inputs, observes the state evolution of the artificial psychological system after receiving these interventions—including outputs such as emotional changes, cognitive responses, and behavioral intentions—and quantifies the effects of different strategies according to preset evaluation criteria, thereby providing data support for the decision-making stage. Evaluation criteria may include the degree of improvement in emotional stability and the degree of reduction in risk indicators.

Decision-making agent: This is the "human–machine collaborative hub," responsible for transforming the outcomes of virtual experiments into safe actions in the real world. This agent generates patient-facing artificial dialogue content, implements gentle intervention measures, and requests confirmation and authorization from human experts at key decision points, such as before the execution of high-risk strategies. At the same time, it also provides human experts with an interface for directly conducting experiments on the artificial psychological system, supporting experts in exploring personalized intervention plans by modifying parameters and designing scenarios, thereby ensuring that the strategy ultimately executed has not only been validated through computational experiments but also incorporates the clinical wisdom and ethical judgment of human experts.

4.2 Workflow

The workflow of PsyRescueGPT follows the ACP approach, proceeding from the construction of the artificial psychological system to computational experiments and then to parallel execution. The following illustrates the logic of this approach through the case of university student Xiao A.

Case background: University student Xiao A has experienced sleep disturbance and social avoidance for two consecutive weeks. A smart wristband has detected relatively low heart-rate variability, and negative expressions such as "failure" and "meaningless" frequently appear in the diary entries on Xiao A' s phone.

Step 1: Construction of the artificial psychological system

At the stage of constructing the artificial psychological system, a large language model is used as the foundation. Through retrieval-augmented generation technology, Xiao A' s historical data and psychological domain knowledge are injected, including past behavioral records, clinical assessment results, cognitive-behavioral theory, crisis-intervention guidelines, and so forth. In this way, an initial artificial psychological system is constructed, enabling the system to possess basic psychological-health reasoning capabilities.

Step 2: Real-time data sensing and system updating

The perception agent continuously collects physiological data from the smart wristband, mobile-phone usage behavior, and diary text content, and converts the multimodal data into standardized feature vectors through a dedicated encoding network. These standardized feature vectors—that is, Xiao A' s personalized data—will be used periodically, via parameter-efficient fine-tuning technology, to update the initial artificial psychological sys—

calibrates the system, forming an artificial psychological system that represents Xiao A' s specific psychological characteristics and provides a unified computational foundation for all subsequent stages.

Step 3: Risk Identification and Predictive Analysis

The prediction agent uses the real-time data collected by the artificial psychological system and the perception agent. Based on Transformer, it predicts the probability of Xiao A' s depression risk over the next 72 hours, and, through the self-attention mechanism of Transformer, analyzes the key risk factors affecting Xiao A. For example, the prediction agent can identify the malignant cyclic pattern of "sleep disturbance—negative cognition—social avoidance," and predicts that Xiao A' s probability of depression risk within the next 72 hours will exceed 68%. Meanwhile, "academic pressure" and "lack of social support" are identified as key risk factors.

Step 4: Generation of Intervention Strategies

Based on the prediction results and key risk factors from the prediction agent, the strategy agent generates structured intervention plans through a predesigned prompt semantic framework. According to Xiao A' s relevant risk factors, this agent generates strategies that include multiple modalities, such as cognitive restructuring dialogues, behavioral activation tasks, and promotion of social connection, ensuring that the plan both conforms to evidence-based practice and possesses personalized characteristics.

Step 5: Verification Through Virtual Experiments

The experimental agent verifies the effectiveness of strategies within the artificial psychological system. By inputting prompt sequences for different strategies, it observes response changes in the artificial psychological system in terms of emotional indicators, cognitive patterns, and behavioral intentions. The experimental results show that a compound strategy combining cognitive restructuring with mild behavioral activation can reduce the probability of depression risk, and that users evaluate its acceptability favorably.

Step 6: Human-Machine Collaborative Decision-Making and Execution

The decision-making agent transforms the verified optimal strategy into an executable plan and generates personalized interaction content for Xiao A. The system automatically generates a decision report and pushes it to the supervising psychological counselor, explaining in detail the intervention logic, expected effects, and risk-control measures. After the counselor reviews and confirms the plan, the system pushes activity recommendations of appropriate intensity and empathic support information to Xiao A through the mobile terminal, and continuously collects feedback data during implementation to form closed-loop optimization.

4.3 Security and Reliability

Given the sensitivity of psychological crisis intervention and mental health, ensuring the security and reliability of PsyRescueGPT is of paramount importance. Based on the collaborative architecture of the artificial psychological system and the five agents, the system is designed with a multilayered security assurance mechanism.

The multi-agent cross-validation mechanism constitutes the system' s foundational safety layer. During the construction of the artificial psychology system, the perception agent ensures the reliability of baseline data through multi-source data fusion; the risk-assessment results produced by the prediction agent must be mutually corroborated with the perception agent' s real-time monitoring data; and the experimental agent conducts safety pre-validation, in a virtual environment, of the intervention plans generated by the strategy agent, thereby minimizing the risk of misjudgment in any single link.

Knowledge-base constraints and evidence-based practice run through the entire process. The construction of the artificial psychology system is based on validated psychological theories and clinical guidelines, ensuring the scientific soundness of the underlying model. All agent operations are conducted within strict knowledge boundaries: the intervention plans generated by the strategy agent must follow the principles of evidence-based intervention; the evaluation criteria of the experimental agent are based on indicators of clinical effectiveness; and the execution logic of the decision-making agent conforms to ethical norms.

Transparency and interpretability are achieved through multi-level explanation mechanisms. The artificial psychology system provides traceable analysis of state evolution; the prediction agent outputs analyses of the contribution of risk factors; the strategy agent provides the theoretical rationale for intervention plans; the experimental agent generates detailed strategy-validation reports; and the decision-making agent integrates information from all parties to provide users and experts with readily understandable explanations of the decision logic.

Privacy protection and compliance are embedded in every aspect of system design. Beginning with data collection by the perception agent, the system uses technologies such as differential privacy (Dwork, et al., 2014) and federated learning (McMahan, et al., 2017) to ensure data security. All data processing complies with regulatory requirements such as HIPAA (Health Insurance Portability and Accountability Act, a U.S. federal law) and the GDPR (General Data Protection Regulation, an EU regulation). While ensuring computational effectiveness, the artificial psychology system implements privacy protection through technologies such as data desensitization and model distillation (Hinton, et al., 2015).

With respect to human–machine collaborative decision-making, a hierarchical decision-making mechanism is designed within the decision-making agent. Fully automated decision-making is applicable only to low-risk scenarios such as the dissemination of psychological science information. Human–machine collaborative decision-making requires that medium-risk intervention strategies be reviewed by human experts, with the decision-making agent providing detailed strategic rationales and validation reports. Human-led decision-making ensures that, in high-risk situations, the system performs only monitoring and early-warning functions, while all intervention decisions remain the full responsibility of human experts. This hierarchical mechanism both safeguards the efficiency of emergency response and ensures human oversight of high-risk decisions.

For possible false positives and false negatives in the system, the framework establishes response plans. In the case of false positives, the system should provide users with a clear explanation, state the reasons for the warning, offer reassurance, and emphasize that the warning is a preventive measure, while maintaining procedural transparency to sustain trust. In the case of false negatives, in addition to establishing redundant monitoring mechanisms, the system should clearly inform users of its own limitations and encourage them to actively seek help when they feel unwell, rather than relying entirely on the sys—

system monitoring. The above safeguards are intended to enable PsyRescueGPT to operate in a manner that is safe, reliable, and respectful of users' autonomy and privacy.

4.4 Application Scenarios

Based on the collaborative architecture of the artificial psychological system and the five agents, PsyRescueGPT can provide methodological support in multiple psychological crisis intervention scenarios, such as suicide risk management, panic-attack prevention, post-traumatic stress disorder (PTSD, Post Traumatic Stress Disorder) management, and routine mental health management. The following takes the scenario of suicide risk management as an example to describe its workflow and data flow.

Current suicide risk management faces multiple challenges. First, suicidal ideation is highly concealed; individuals often deliberately hide their true thoughts, which makes traditional methods that rely on self-report and clinical interviews lag behind. Although studies show that more than 80% of people who die by suicide exhibit identifiable warning signs before the event, these signals are distributed across multiple dimensions, including physiology, behavior, and language. Existing systems lack effective multimodal data-fusion capabilities, making it difficult to capture risk indicators comprehensively. Meanwhile, generalized intervention plans are unable to meet individualized needs, lack mechanisms for validating the prospective effects of intervention strategies, and cannot dynamically adjust intervention intensity according to individual characteristics. In terms of real-time response, there is a significant time delay from risk identification to professional intervention; the allocation of crisis resources lacks precise guidance; and there is a lack of systems for continuous risk tracking and effect evaluation. These challenges require a methodological framework capable of early warning, precise intervention, and continuous optimization.

As shown in Figure 4, for the suicide risk management scenario, during the preparation stage, the system first constructs an initial artificial psychological system based on the individual' s historical data and domain knowledge in psychology, using retrieval-augmented generation technology and parameter-efficient fine-tuning methods; this serves as the computational foundation of the overall framework. During the operation stage, the perception agent continuously collects multimodal data such as expressions of despair in the user' s language, socially isolated behaviors, and physiological stress indicators, and transforms these heterogeneous data into unified feature representations through specialized encoding networks, thereby providing fused multimodal data input for the artificial psychological system. While being dynamically updated, the artificial psychological system outputs an integrated psychological state and historical trajectory of evolution. The prediction agent then, based on the real-time data from the perception agent and the psychological-state evolution trajectory of the artificial psychological system, quantitatively evaluates the risk level over the next 24–72 hours and identifies key influencing factors, and sends the risk-identification information and influencing factors to the strategy agent.

The strategy agent generates hierarchical intervention plans according to the influencing factors and risk levels, including hierarchical strategies such as scripts for safety confirmation and emotional soothing dialogues, crisis-hotline connection and social-support activation, and referral processes involving emergency contacts and professional institutions. It also generates strategy-related prompts and sends them to the experimental agent. The experimental agent inputs these strategy-related prompts into the artificial psychological system to conduct simulation and validation of the strategies, and evaluate each

the effects of strategies in regulating risk indicators, ensuring that the plan is both safe and effective, and generate experimental reports and effect analyses. Finally, based on the experimental reports and effect analyses, the decision-making agent initiates the corresponding human–machine collaborative processes, ranging from the automatic pushing of support information for low-risk cases to the activation of emergency intervention protocols for high-risk cases. Through continuous system operation and interaction with physicians and users, the system is dynamically updated and optimized, including updates to the artificial psychological system, relevant knowledge bases, and strategy bases.

Preparation stage

User historical data; domain knowledge
↓ Inject into the large model

Initial construction of the artificial psychological system
↓ Initial artificial psychological system

Operation stage

User → real-time data → monitoring agent
Monitoring agent → fused data → dynamically updated artificial psychological system
Monitoring agent → fused data → prediction agent
Prediction agent → risk prediction and cause analysis → strategy agent
Dynamically updated artificial psychological system comprehensive psychological state strategy agent
Decision-making agent → real-time testing → dynamically updated artificial psychological system
Dynamically updated artificial psychological system → state feedback → decision-making agent
Strategy agent → intervention strategies and model prompts → experimental agent
Experimental agent → computational experiments and effect simulation → dynamically updated artificial psychological system
Experimental agent → effect analysis and experimental reports → decision-making agent
User, physicians, relatives, and friends → communication interface → decision-making agent

Figure 4. Workflow and data flow for suicide risk management

5 Discussion and Prospects

The parallel psychological-crisis intervention framework and the PsyRescueGPT prototype system provide an envisioned methodological framework and implementation pathway for addressing the dynamism, complexity, and need for personalization in the field of psychological-crisis intervention.

5.1 Theoretical Significance and Contributions

This paper explores the introduction of parallel intelligence theory into the field of psychological-crisis intervention. By transforming subjective and dynamic psychological states into computable objects that can be modeled, predicted, and intervened upon, it proposes a parallel psychological-crisis intervention framework based on "artificial systems–computational experiments–parallel execution," providing a preliminary methodological framework and potential technical implementation pathway for studying complex psychological phenomena and psychological-crisis intervention.

The emergence and development of psychological crises involve the dynamic interaction of multidimensional factors such as physiology, behavior, cognition, and context, constituting a typical complex system (James & Gilliland, 2025).

The proposed parallel framework attempts, through the construction of an artificial psychological system, to map this complex system into a computable and operable object, thereby offering a new methodological perspective for exploring the internal mechanisms of psychological crises. The computational-experiment component in the framework enables research

⋯can conduct repeated simulations and safety validation of intervention strategies in a virtual environment, thereby reducing the ethical risks and uncertainties of direct human experimentation and providing a potentially safe and effective pathway for optimizing intervention plans (Bosk, 2023).

In terms of implementation, PsyRescueGPT combines large language models with a multi-agent architecture. This prototype system can not only dynamically assess psychological states (Bunt et al., 2025; Pellert et al., 2024), but also, through the division of labor and collaboration among multiple agents, cover the entire process from risk perception to decision execution. This design is expected to address several challenges currently faced by LLMs in psychological applications. For example, introducing domain knowledge through retrieval-augmented generation (Ravenda et al., 2025) can enhance the standardization and interpretability of assessments; and a human-in-the-loop decision-making mechanism can attempt to balance the efficiency of automated decision-making with the clinical judgment of human experts, so as to avoid risks arising from potentially inappropriate responses generated by LLMs (Stade et al., 2024). It is worth further noting that the agents in this framework, because they are deeply embedded in the ACP process and uniformly driven by the computational foundation of the artificial psychological system, already differ in their mode of operation from traditional task-oriented agents. Their "parallel" characteristics are reflected in collaborative operations across virtual and real spaces and in their capacity for continuous evolution.

5.2 Practical and Applied Value

At the level of practical application, this framework has preliminarily demonstrated a certain degree of potential. It is applicable not only to acute psychological crisis scenarios such as suicide risk (Garriga et al., 2022), panic attacks, and post-traumatic stress disorder, but can also be extended to preventive intervention domains such as everyday mental health maintenance, stress management, and emotion management. It is expected to play a multi-level role within the public mental health service system.

This framework may also provide a feasible pathway for addressing the current shortage of psychological service resources (Yao et al., 2022). Studies have shown that the response quality of LLM-based counseling dialogue systems can be comparable to that of human counselors (Ferrario et al., 2024). This suggests that the strategy agents and decision-making agents in PsyRescueGPT may, under the premise of ensuring safety, undertake part of the standardized psychological support work, thereby expanding service coverage. For example, the system can provide continuous, low-cost dynamic monitoring and mild intervention support for individuals waiting for counseling or undergoing rehabilitation.

5.3 Limitations and Future Directions

Although this framework shows promise, its development and application still face several limitations and challenges that urgently need to be addressed.

First, insufficient clinical validity and validation constitute the most important current limitation. The reliability of the system' s core component—the artificial psychological system—and the effectiveness of the intervention strategies generated from it urgently need to be tested in real clinical settings through

validated through rigorously designed randomized controlled trials (Bosk, 2023). Future research should collaborate with clinical institutions to conduct multicenter, large-sample, long-term follow-up studies, collecting multidimensional data from the intervention process through long-term outcomes, in order to test and optimize the system' s generalizability and long-term benefits (Nahum-Shani et al., 2016).

Second, challenges remain at the level of technical implementation. On the one hand, system operation—especially the training and inference of complex models—places relatively high demands on computing resources, which may constrain its dissemination in resource-limited settings. Future work should explore pathways such as model lightweighting and edge-computing deployment (Han et al., 2016) to improve usability. On the other hand, data privacy and algorithmic security are issues that must be given the highest priority. In addition to the privacy-preserving technologies already discussed in this article, it is also necessary to remain alert to high-level security risks; for example, when large language models are subjected to specific attacks, their safety safeguards may be substantially bypassed (Carlini et al., 2017). This requires that real-time security monitoring and defense mechanisms be integrated into system design to ensure that generated content is safe and reliable.

The construction of ethical and governance frameworks also requires deeper development. Parallel psychological crisis-intervention systems involve the continuous collection and deep computation of sensitive psychological data. How to strike a balance between technological innovation and ethical constraints is therefore key to promoting their responsible development (Hartzog et al., 2018). Future work should bring together ethicists, clinical experts, legal practitioners, and community representatives to jointly formulate cross-cultural and cross-population ethical principles and governance frameworks covering data sovereignty, algorithmic transparency, the delineation of responsibility, and safeguards for fairness (Lawrence et al., 2024).

In-depth exploration of the agent paradigm. The agents in the framework proposed in this article are deeply integrated into the ACP process, and their mode of operation already exhibits the "parallel" characteristics of collaboration and evolution across virtual and real spaces. In the future, such agents can be more formally defined and modeled, and systematically compared with traditional task-oriented agents, thereby exploring the establishment of a new paradigm of "parallel agents." This is also a valuable research direction for further enriching the theory of parallel intelligence.

Through sustained technological optimization, rigorous clinical validation, and prudent ethical governance, the parallel psychological crisis-intervention framework and PsyRescueGPT are expected to move from a methodological framework and implementation concept toward practical application, ultimately developing into a new generation of human-centered, precisely controllable, and self-evolving mental health service platform.

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Gong Xiaoyan: proposing the research topic; drafting and revision of the parallel psychological crisis intervention framework section.

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