# A SECI-Based Multi-Agent Framework for Transforming Generative-AI Interaction Logs into Collective Intelligence

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***Abstract*—In this study, we define the user-specific tacit elements embedded in generative-AI use as *tacit knowledge* and propose a system that supports organizational collective intelligence by converting and sharing them as *explicit knowledge* based on the SECI model. Specifically, we construct each SECI process (Ba) as a multi-agent system to improve the autonomy and sustainability of the knowledge-creation process. Regarding the proposal system, we implemented the process equivalent to Socialization as a web application, and designed and evaluated the other processes (Externalization to Internalization) as prototypes on an API platform. The pilot study verified that parts of the process from socialization to internalization were observed. This suggests that the accumulation of further case studies may solidify the utility of this system. These results indicate that this system has the initial feasibility to be an effective foundation for promoting and supporting organizational knowledge creation.**

***Index Terms*—collective intelligence, generative AI, LLM, information reuse, SECI model, knowledge acquisition**

## I. Introduction

With recent advances in generative AI such as ChatGPT [1] and Claude [2], interacting with generative AI has attracted attention as a problem-solving approach across a wide range of domains, including natural language processing, programming error handling, and creative content production [3]. However, a prior study [4] pointed out the following two issues regarding the practical use of generative AI's problem-solving capabilities.

**P1: Fragmentation of problem-solving capability due to differences in users' prompt-construction skills for effectively leveraging generative AI**

**P2: Lack of mechanisms for effectively sharing and utilizing interaction logs within an organization**

To address these issues, a web application called **ChatHubAI** (hereafter **CHAI**) has been proposed and developed to accumulate and share conversations with generative AI together with their context and usefulness, thereby fostering organizational collective intelligence [5]. CHAI primarily focuses on functions for accumulating and sharing dialogue logs with generative AI, and has successfully implemented these functions. However, the processes of "knowledge conversion" or the "knowledge creation spiral"—such as extracting insights from accumulated logs, connecting them with other insights, and re-injecting them into subsequent practice—still depend heavily on manual work by users. As a result, even if logs are sufficiently accumulated, the challenge remains that it is difficult to operate them in a way that circulates and deepens them as organizational collective intelligence.

In this study, we define the insights gained through the use of generative AI as *tacit knowledge* and focuses particularly on the implicit know-how and context behind dialogue logs, such as prompt-tuning techniques and context-based judgments of usefulness. Based on the SECI model, this study proposes a system that supports the development of organizational collective intelligence by converting and sharing such knowledge as "explicit knowledge." As its approach, this study constructs each process, or "ba," of the SECI model as a multi-agent system, thereby autonomously supporting and automating the knowledge conversion tasks that have traditionally been performed by users.

## II. Preliminaries

### A. SECI Model

The SECI model [6], proposed by Nonaka et al., is a knowledge-management framework that explains how individual knowledge is shared and leveraged across an organization and how new knowledge is created. Recent work also discusses how large language models can accelerate SECI-like knowledge-creation cycles [10]. The model defines that knowledge deepens and expands as the following four processes (Ba) circulate in a spiral manner (the knowledge-creation spiral).

- **Socialization:** Transfer of tacit knowledge through sharing experiences.
- **Externalization:** Articulation of tacit knowledge into explicit knowledge through dialogue and metaphors.
- **Combination:** Systematization by combining multiple pieces of explicit knowledge.
- **Internalization:** Acquisition of new tacit knowledge through practice of systematized knowledge.

### *B. Ba: Shared Context for Knowledge Creation*

Nonaka et al. also proposed the concept of *Ba* as a shared context in which the knowledge-creation process functions [7]. Ba is not merely a physical space; it refers to a dynamic context (shared time and space) in which individuals interact and knowledge is created, shared, and utilized. Each process in the SECI model has a corresponding Ba.

- **Originating Ba:** A place where individuals directly share dialogue and experiences and exchange tacit knowledge.
- **Interacting Ba:** A place where mental models and skills are shared and articulated as common concepts.
- **Cyber Ba:** A virtual place where explicit knowledge is combined to build a large-scale knowledge system.
- **Exercising Ba:** A place where explicit knowledge is transformed back into tacit knowledge through practice.

### *C. Tacit and Explicit Knowledge*

Knowledge can be broadly categorized into *tacit knowledge* and *explicit knowledge* based on its expressibility. Tacit knowledge refers to knowledge grounded in personal experience, intuition, and subjective insights that is difficult to verbalize or structure. In contrast, explicit knowledge is knowledge expressed objectively and systematically through text, formulas, figures, etc., and is easy to communicate to others.

*1) Knowledge Characteristics of Generative-AI Interaction Logs:* In this study, we defineinteraction logs are not treated as tacit knowledge per se; rather, they are treated as artifacts that contain traces of users ’ *tacit knowledge* While the AI output itself is verbalized, the fine-tuning of prompts (know-how) that elicited the output and the context that led the user to judge a particular answer as useful strongly depend on the user's subjectivity. Therefore, we argue that extracting essential insights—*why* a certain result was obtained—from these fragmented logs and structuring them into a reusable form corresponds to *externalization* and *combination* in the SECI model and is key to forming organizational collective intelligence.

### *D. Related Work: ChatHubAI*

As prior research, we developed CHAI [8], a service for accumulating and sharing interaction logs with generative AI and their context. CHAI implements functions corresponding to the Interacting, Cyber, and Exercising Ba: a chat function for problem-solving, an Interacting Ba function that captures dialogue intents based on 5W2H, and a Cyber Ba management function for evaluating and searching logs. However, it lacks an Originating Ba function to facilitate tacit-knowledge sharing and trigger interactions. Moreover, knowledge transformation tasks—extracting insights, identifying patterns across cases, and determining how to apply them to new problems—still depend heavily on users' manual efforts. As a result, logs accumulate without deepening into genuine collective intelligence.

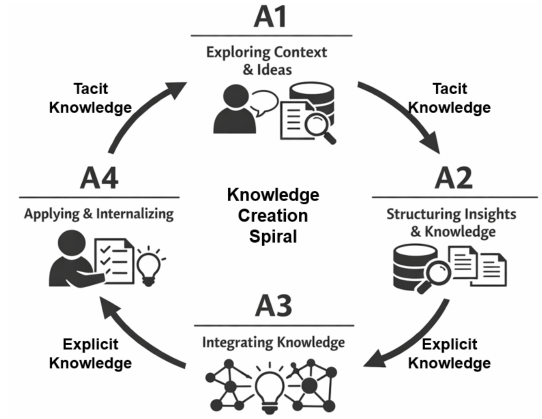


Fig. 1. Overall architecture

## III. Proposed Method

### *A. Objective and Key Idea*

The objective of this study is to build a mechanism that autonomously and sustainably converts and circulates tacit knowledge hidden in massive interaction logs with generative AI into organizationally reusable knowledge (explicit knowledge).

The key idea is to virtually construct and autonomize the knowledge-creation *Ba* in the SECI model using a multi-agent system. Concretely, we place agents specialized for each knowledge-conversion process in the corresponding Ba. By coordinating these agents, the system realizes a spiral in which insights are extracted from interaction logs, organized, and re-provided without imposing excessive structuring burdens on users. In this method, we define the approach as a set of agents corresponding to the following four Ba.

- **A1: Originating-Ba**
- **A2: Interacting-Ba**
- **A3: Cyber-Ba**
- **A4: Exercising-Ba**

The overall architecture is shown in Fig. 1.

### *B. (A1) Originating-Ba*

The agent generates a structured report describing the task and its context and posts it to the organization's communication platform, for example Slack [11], and it automatically creates a dedicated thread for problem solving, and the agent participates as a facilitator. By proposing new perspectives when discussion stagnates and encouraging other members to

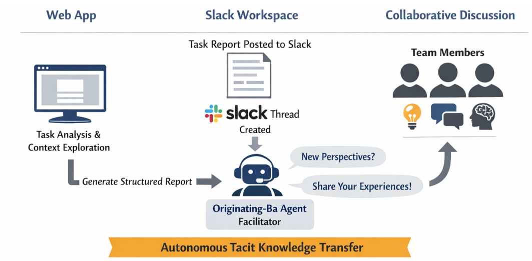


Fig. 2. A1 architecture

articulate experiential knowledge, the agent induces interactions in the *originating Ba*. As a result, know-how for using generative AI, which previously remained within individual trial-and-error, is elevated into an autonomous tacit-knowledge transfer process within the organization. The A1 architecture is shown in Fig. 2.

### C. (A2) Interacting-Ba

It builds a *task-solution case database* for each task and registers, in addition to detailed interaction logs with generative AI, metadata such as the worker's realizations and insights obtained during problem solving. The agent then performs dialogue-structure analysis on the accumulated information to automatically extract (i) the core theme of the task, (ii) prompt patterns that contributed to the solution, and (iii) key insight keywords. This supports a process that goes beyond merely storing logs: it systematically organizes tacit insights obtained by users and transforms them into explicit knowledge that other members can reuse by integrating context with insights.

### D. (A3) Cyber-Ba

It compares and analyzes solution structures and metadata obtained from different users and tasks, and performs knowledge clustering and extraction of composition patterns. This enables the system to present a user's success case not merely as a record but as a *question-formulation method (meta-prompt)* or *logical composition model* that can serve as a starting point for another user's thinking and exploration. Furthermore, by actively recommending knowledge based on similarity and complementarity between pieces of knowledge, it encourages the creation of new knowledge by combining existing knowledge and stimulates problem posing for latent issues. Through these functions, the system realizes an autonomous process that combines and edits scattered individual experiential knowledge in the *cyber Ba* and elevates it into organizational collective intelligence.

### E. (A4) Exercising-Ba

It provides adaptive support for new tasks to which the presented knowledge should be applied, according to the user's proficiency. The agent assesses the user's understanding through dialogue: if the understanding is sufficient, it encourages continued advanced trial-and-error with generative AI to promote the acquisition of practical know-how. If the understanding is insufficient, it provides basic explanations and guides the user to re-discussion in the originating Ba, preventing stagnation due to knowledge mismatch. In addition, to encourage learning of the recommended knowledge, the agent offers a reflection-support function that asks users to redefine the insights in their own words after solving the task. This prevents explicit knowledge from being consumed as mere information and autonomously completes internalization as a process that becomes part of the individual's practical competence.

## IV. Implementation

To validate the proposed system, we implemented a prototype of the multi-agent system. In particular, we implemented the (A1) as a working system because it requires collaboration and is responsible for triggering organizational discussion, while the other processes were configured as simulations on an API platform.

As the core reasoning model for the agents, we used **GPT-5-mini (gpt-5-mini-2025-08-07)**. This model provides both strong reasoning capability and low latency, enabling high-quality outputs especially for context probing in (A1) and dialogue-structure analysis in (A2).For agents other than (A1) (A2–A4), we used prompts based on the CHAI design to explore their processing capabilities for the data passed from (A1).

## V. Evaluation

To evaluate the effectiveness of the proposed system, we conducted a single-case pilot study with one of the authors as the subject [9] using an abstract problem-solving task: *designing learning materials that enable beginners with no experience in "Vibe Coding" to become self-sufficient*.

### A. Procedure

- (A1): The subject inputs the initial task. The agent probes missing context, and develops a discussion on Slack. The subject provides reflections on the interaction to capture the externalization of tacit knowledge.
- (A2): The agent structures and extracts the insights from the Slack discussion and the interaction logs with the AI.
- (A3): The agent synthesizes the extracted insights and outputs a problem statement.
- (A4): The subject performs a reflection to internalize new knowledge based on the A3 output. Subjective feedback is collected to verify if the knowledge has been successfully internalized as new tacit knowledge. *new issues (exercises)*.

### B. Results

In the reflection for (A1), the following feedback was received: "I was able to learn tacit knowledge such as the amount of time beginners can spare per week and their tendency to favor practice over theory, which was helpful for designing learning materials. Also, I believe the discussion became more active because the agent facilitated it."

As a result of structuring by the (A2) agent, ten important tips were extracted (Table I). In particular, core concepts for learning-material design, such as *backward design* and a *two-phase structure*, were organized. The system also suggested a structural approach to curriculum design: "everyone first builds the same artifact" → "then each person develops an original artifact according to their interests."

TABLE I
EXTRACTED TIPS (IN ORDER OF PRIORITY)

| Priority | Keywords / Description |
|---|---|
| High | **Backward design**, minimal app, standard stack |
| Medium | **Two-phase structure** (conceptual understanding → implementation experience) |
| | **Learning cycle** (common hands-on → original development) |
| Low | **Mindset** (feature-oriented development, self-sufficiency) |

The issues identified in (A3) included *the challenge of determining standard specifications for a minimal web application*, *the challenge of designing the transition from hands-on materials to original projects*, and *the challenge of designing learning progress and the granularity of deliverables for a schedule of two hours per week*.

As for the reflection in (A4), comments were received such as "I believe the insights gained in A1 were useful even for high-granularity tasks."

## VI. DISCUSSION

This study confirmed that (A1) the exploration of tasks by the emergent-field agent effectively facilitated the verbalization of the worker's context and constraints, proving highly effective in transforming tacit knowledge into explicit knowledge. This not only improved the accuracy of responses but also ensured the accumulation of high-quality explicit knowledge that includes background information. On the other hand, (A3) the integration of insights during the Cyber Ba remained limited to suggesting the next steps under single-task conditions and did not reach the creation of new knowledge that spans multiple contexts. The cultivation of collective intelligence requires the accumulation of cases from diverse users.

### A. Limitations

- **Implementation scope:** The implementation focused primarily on the process corresponding to the field of emergence, while the functions corresponding to externalization and internalization remain at the stage of design and evaluation as a prototype on the API platform. Ideally, the approach should be embodied as a complete integrated system, and its effectiveness needs to be verified.
- **Evaluation design:** This experiment aimed to verify operation and identify issues, rather than validating the effectiveness of the method itself. It is necessary to conduct experimental design with an appropriate number of participants and an adequate experimental period for evaluation purposes.
- **Organizational collective intelligence claims:** Genuine organizational collective intelligence requires diverse users and longitudinal deployment. Our single-subject pilot cannot substantiate organizational-level formation.

## VII. CONCLUSION

In this study, we regarded interaction logs with generative AI as tacit knowledge and proposed a multi-agent system that transforms them into organizational collective intelligence based on the SECI model. Results from implementing a prototype and conducting a pilot study indicate that, in particular, it was suggested that the knowledge creation process could circulate autonomously by functioning effectively, particularly in Originating-Ba and Interacting Ba. Furthermore, it was shown that the Originating-Ba helps improve the quality of problem-solving by assisting in the transfer of tacit knowledge. As a future prospect, we plan to integrate and implement a group of agents corresponding to externalization and internalization as a web application that is easy for users to participate in, and introduce it into an organizational environment for the long term. Through this, we intend to verify quantitatively and qualitatively how the linking and reconstruction of knowledge across diverse dialogue logs deepens collective intelligence.

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