IIAI Open Conference Publication Series
IIAI Letters on Informatics and Interdisciplinary Research
Vol.006, LIIR351
DOI: https://doi.org/10.52731/liir.v006.351

# Digital Knowledge Twin: Bridging the Gap Between Physical and Cyber Knowledge Spaces by Generative AI

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## Abstract

The extraction, sharing, and utilization of explicit, latent, and tacit field knowledge (called "Gen-Ba knowledge") possessed by skilled workers in fields such as healthcare, caregiving, agriculture, maintenance and inspection, and manufacturing, have long been recognized as important yet challenging tasks. Organizations and companies capable of achieving this through human systems hold a competitive advantage. With the advent of generative AI, explicit knowledge that can be codified (documented) has become dramatically more accessible. However, the challenge remains in how to efficiently and effectively handle the latent and tacit Gen-Ba knowledge possessed by humans, which AI cannot directly process. This study proposes a "Digital Knowledge Twin", which facilitates externalization, combination, and internalization of Gen-Ba knowledge for bridging the gap between physical and cyber spaces. In the externalization phase, Gen-Ba knowledge is accumulated in the physical space as fragments of knowledge, integrating human voice messages, photos, and physical sensor data. Then, these Gen-Ba knowledge fragments are linked with structure of operations in the cyber space in a combination phase. Finally, Gen-Ba knowledge is collaboratively internalized in the physical space through workshops, where internalization means sensemaking and symbol grounding among humans. This paper presents the necessary technologies and system architecture required for the implementation of the "Digital Knowledge Twin." Gen-Ba knowledge management using generative AI is a challenging issue, and the theoretical contribution of this study is that it provides one promising research direction of future knowledge management.

*Keywords:* Digital Knowledge Twin, Gen-Ba Knowledge Management, Generative AI

## 1 Introduction

This paper explores the utilization of generative AI in managing latent and tacit field knowledge, which is challenging to manage. The recent development and widespread adoption of generative AI based on large language models (LLMs) have significantly transformed the knowledge management of explicit knowledge. However, various fields such as healthcare, caregiving, agriculture, maintenance and inspection, and manufacturing possess vast amounts of latent and tacit field knowledge that are difficult to manage. This paper refers to explicit, latent, and tacit field knowledge as "Gen-Ba knowledge" [1]. In Japanese, "Gen" means "actual and physical field," and "Ba" means "knowledge creating space," which is introduced by Nonaka and Takeuchi [2, 3]. Gen-Ba knowledge consists of three layers (Fig. 1): explicit, latent, and tacit knowledge, with boundaries that are continuous and not clearly delineated. A significant portion of Gen-Ba knowledge is latent and tacit, making it challenging to verbalize. Despite advancements in LLMs, generative AI can only handle verbalized knowledge, leaving a substantial gap

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between a physical knowledge space (explicit, latent, and tacit knowledge) and a cyber knowledge space (verbalized explicit knowledge). In the era of generative AI, verbalized knowledge becomes commoditized, while non-verbalized knowledge becomes the source of competitiveness. Gen-Ba knowledge has traditionally been a strength of Japanese companies, particularly in integrative product development such as in the automotive industry, maintaining global competitiveness. However, this does not imply that the management of Gen-Ba knowledge can remain as it is.

The objective of this paper is to propose a concept for utilizing generative AI to achieve efficient and effective management of the extraction, sharing, and utilization of Gen-Ba knowledge. This paper specifically focuses on explicit and latent Gen-Ba knowledge. Here, latent knowledge refers to knowledge that, although not formalized in an organized manner like manuals, can be verbalized, albeit imperfectly, when asked in certain field situations. Tacit knowledge in its narrowest sense that is inherently difficult to verbalize and embodied in physical actions, such as "how to ride a bicycle," is beyond the scope of this paper. However, in a broader sense, tacit knowledge also encompasses latent knowledge [2]. Additionally, this paper aims to enumerate the technologies necessary to realize this concept and to indicate future research directions.

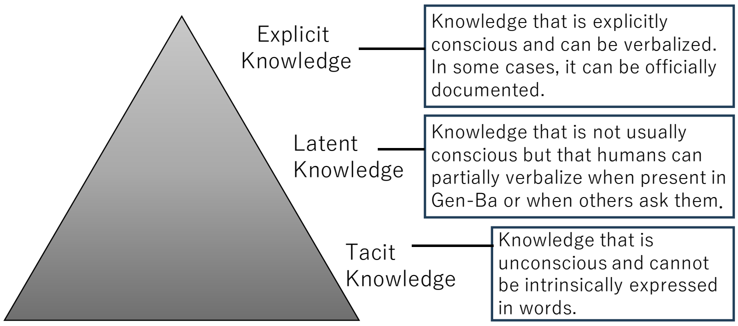


Figure 1: Continuous Gen-Ba Knowledge Layers [1]

The concept proposed in this paper is named the "Digital Knowledge Twin." This system aligns knowledge from the physical space with knowledge in the cyber space, supporting the extraction and utilization of Gen-Ba knowledge by leveraging the advantages of cyber space. Here, the primary agents in the physical space are humans, while in the cyber space, they are computers. The Gen-Ba knowledge that humans possess in the physical space is interpreted and verbalized with a specific meaning, a process known as symbol grounding. This grounded knowledge is inputted into the cyber space and accumulated there. Then, accumulated knowledge is reinterpreted and utilized back in the physical space. Symbol grounding is a task that only humans can perform and AI cannot (symbol grounding problem). However, AI can assist in the interface tasks between the physical space and the cyber space, and there are technological development elements necessary for this support.

The structure of this paper is as follows. Chapter 2 reviews previous research and identifies research gaps. Chapter 3 proposes "Digital Knowledge Twin" for managing Gen-Ba knowledge using generative AI. Chapter 4 enumerates technological functions to be developed for realizing this concept. Chapter 5 explains the concept using an illustrative example. Chapters 6 and 7 provide discussions and conclusions.

# 2 Literature Review

## 2.1 Knowledge Management

There is a vast body of research on knowledge management and knowledge management systems [4,5]. Traditionally, knowledge management systems utilizing digital technologies have primarily focused on explicit knowledge (codified knowledge), and many companies have employed knowledge databases of best practices [5].

Regarding the management of tacit knowledge, SECI (Socialization, Externalization, Combination, and Internalization) model has helped explain the strengths of Japanese firms [2]. In the field of knowledge management research, studies have addressed not only the management of explicit knowledge but also the management of latent and tacit knowledge [6,7,8,9]. However, many of these studies focus on supporting communication among members through IT, and while machine learning-based modeling and the visualization of latent and tacit knowledge are positioned as functions to support human knowledge management, there is limited research on knowledge management and systems utilizing generative AI. Specifically, Hu et al. [10] have organized the opportunities and challenges of applying ChatGPT to design knowledge management, but they do not address the latent and tacit field knowledge targeted in this study. When dealing with generative AI, the issue of symbol grounding arises. Humans are responsible for symbol grounding, and generative AI and systems are positioned to support this process. However, the methods of support remain a significant challenge in knowledge management research.

## 2.2 Digital Twin and Human Digital Twin

The term “Digital Twin” has several definitions [11], but in this study, it refers to a dynamic digital replica of the physical space in the cyber space. In a Digital Twin, digital data collected from the physical space through IoT is used to virtually recreate physical products and systems in the cyber space, enabling the prediction of various future events [12]. The components of a Digital Twin include “data,” “models,” and “interfaces,” which allow for the simulation and prediction of the state and behavior of the physical space within the cyber space, providing optimal solutions for the physical space. Digital Twins in the manufacturing sector have been extensively studied, particularly in the context of Industrie 4.0. Recently, their applications have expanded to fields such as healthcare, meteorology, environment, energy, and urban planning.

Human data in the physical space is also a crucial element of Digital Twins, known as “Human Digital Twins” [13,14]. For example, data from factory workers can be used to create models of workers in the cyber space, providing feedback on optimal collaboration plans between workers and automated guided vehicles (AGVs) or robots. However, the primary focus of Human Digital Twins is the utilization of physical human information (behavioral and vital information) in the cyber space, particularly in manufacturing and healthcare, and does not address Gen-Ba knowledge of humans.

On the other hand, Japan's Society 5.0 emphasizes the realization of a “human-centered society” by integrating cyber space and physical space. Umeda et al. [15] proposed the concept of “Digital Triplet,” which integrates the space of human intellectual activities into both physical and cyber spaces. This system analyzes data extracted from the physical space in the cyber space and actively incorporates and utilizes human intellectual activities. This approach leverages humans with Gen-Ba knowledge within the cyber space. Furthermore, the “Human-Centered Digital

Twin” has been selected as an open research theme in the “Realization of the Next-Generation Information Society” of the JST-MIRAI project, with six research projects currently underway. However, neither the Digital Triplet nor the current efforts in Human-Centered Digital Twins address the issue of the vast amount of Gen-Ba knowledge embedded in the physical space, leaving this problem unresolved.

Since 2010, we have been conducting research on the management of Gen-Ba knowledge using voice messages as human sensors (Smart Voice Messaging System [16]) that capture various information and knowledge perceived by workers in fields such as healthcare, caregiving, agriculture, maintenance and inspection, and manufacturing. We have demonstrated the effectiveness of this approach in various fields. Additionally, we proposed the “Human-Centric Digital Twin” [1,17], which integrates voice messages with physical sensors as a Digital Twin. However, effective structuring and internalization of Gen-Ba knowledge require human systems (such as workshops) involving the field, and efficiency to avoid excessive burden on the field for continuous implementation has been a significant challenge. To address this challenge, we conceived the idea of the “Digital Knowledge Twin,” which leverages the revolutionary advancements in LLMs and generative AI to reduce the human burden and fill the gaps between the physical space and cyber space.

# 3 Proposal of Digital Knowledge Twin

## 3.1 Challenges of Digital Knowledge Twin

The challenges in realizing the “Digital Knowledge Twin” are as follows (Fig. 2). Here, externalization, combination, and internalization are phases of the knowledge creation process (SECI model) [2]. It should be noted that the socialization phase of the SECI model is already practiced in Japanese workplaces (a strength of Japanese companies) and is not the challenge of this study.

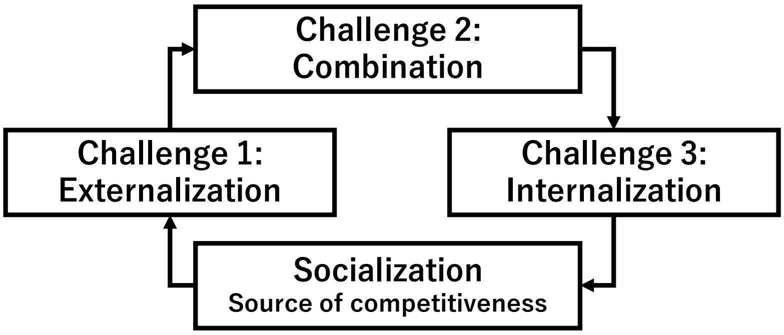


Figure 2: Challenges of Digital Knowledge Twin in SECI Model

1. Externalization Challenge: Externalizing latent and tacit Gen-Ba knowledge is not easy. The process of codifying this knowledge requires considerable effort, and much knowledge remains uncodified in the field.

2. Combination Challenge: Organizing and systematizing the externalized Gen-Ba knowledge into a usable form and accumulating it is not easy and requires significant human effort, posing a substantial burden on the field and hindering sustainable operation of knowledge management.

3. Internalization Challenge: The knowledge that has been organized and systematized is not sufficiently utilized in the field. This is because it is difficult to search for knowledge that fits the field's issues and needs, requiring effort to obtain appropriate knowledge. Although generative AI has the potential to address this challenge, merely codified knowledge (symbols) that is not grounded in the field does not facilitate internalization as one's own knowledge.

The Digital Knowledge Twin proposed in this paper is a concept aimed at addressing these three challenges through the collaboration of AI and human systems to extract, share, and utilize Gen-Ba knowledge. Traditional research on the externalization of human knowledge using digital technologies has primarily focused on converting and supporting the use of knowledge representations with clear semantics, such as ontologies. However, this approach requires substantial effort for implementation and struggles to handle latent and tacit knowledge.

In the Digital Knowledge Twin, instead of converting latent knowledge into knowledge representations with clear semantics, it is externalized as Gen-Ba knowledge fragments that tolerate incompleteness. These fragments undergo loose Gen-Ba structuring (combination) in the cyber space and are internalized through "collaborative symbol grounding" within human systems such as workshops. This entire process leverages LLMs and generative AI to support the efficient and effective extraction, sharing, and utilization of Gen-Ba knowledge.

This approach has the potential to break through the challenges of managing Gen-Ba knowledge (challenges 1, 2, and 3). While research on applying LLMs and generative AI to knowledge management is increasing, it primarily focuses on explicit knowledge. Approaches targeting latent knowledge are rare, making this study unique.

### 3.2 Concept of Digital Knowledge Twin

This paper proposes the Digital Knowledge Twin, a system designed to facilitate the extraction, sharing, and utilization of Gen-Ba knowledge (Fig.3), and identifies the necessary technologies for its implementation. The Digital Knowledge Twin consists of a physical knowledge space and a cyber knowledge space. Here, a knowledge space is defined as a space where knowledge exists. The physical knowledge space refers to the space within humans and organizations where knowledge resides, while the cyber knowledge space is the space where this knowledge is stored in a computational environment. The physical knowledge space and the cyber knowledge space have a Digital Twin relationship. It should be noted that this concept differs from the knowledge space in mathematical psychology.

For the extraction, sharing, and utilization of Gen-Ba knowledge, it is essential to have a system and mechanism that incorporates the generative AI while also involving humans in the process of symbol grounding in the internalization workshop. Specifically, the following research tasks in Figure 3 will be undertaken.

A) Multimodal Gen-Ba Knowledge Externalization (Challenge 1)
By having skilled workers (experts) present in the field, Gen-Ba knowledge, which includes insights and recollections, is recorded and accumulated through various media including voice messages (human sensor data) and physical sensor data.

B) Loose Gen-Ba Knowledge Combination (Challenge 2)
Without seeking perfection, knowledge is systematized with minimal effort to effectively utilize generative AI.

C) Human-AI Collaborative Gen-Ba Knowledge Internalization (Challenge 3)
Efficient and effective internalization of Gen-Ba knowledge in the internalization workshop among experts and non-experts through human-AI collaboration.

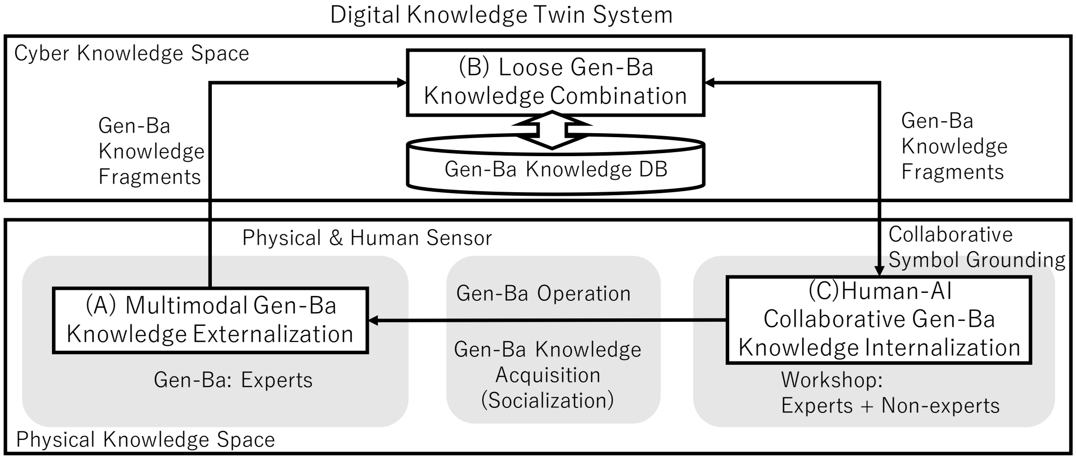


Figure 3: Concept of Digital Knowledge Twin

# 4 Technologies to be Developed

The technologies required to realize the Digital Knowledge Twin are illustrated in Figure 4. This is only one form of implementation of the proposed concept; other implementations are also possible.

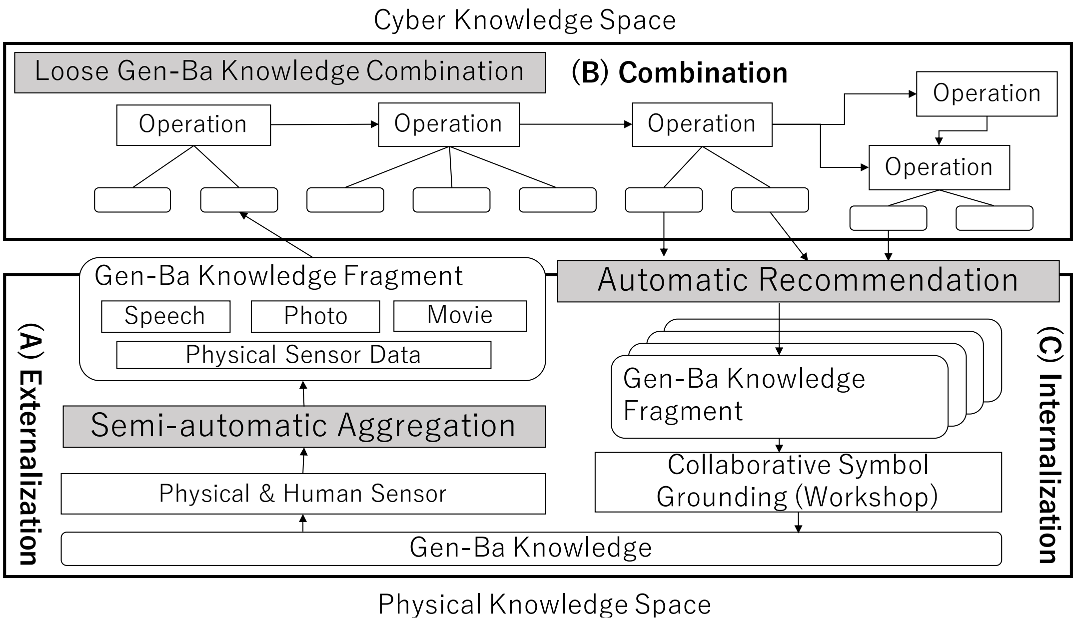


Figure 4: Implementation of Digital Knowledge Twin

### (A) Semi-automatic Aggregation in Externalization

We have extended the Smart Voice Messaging System, developed since 2010 as a human sensor to collect the awareness of skilled workers through voice messages and photos [16]. This extension allows for the multifaceted recording and accumulation of voice messages, photos, and physical sensor data in the field. In our previous research, the aggregation of voice messages, photos, and physical sensor data (Gen-Ba knowledge fragment) was manually performed by humans, which was a significant burden [17]. The proposed concept requires a semi-automated aggregation technology that leverages generative AI to interactively and quickly consolidate Gen-Ba knowledge fragments that can be collaboratively symbol-grounded in workshops (C).

### (B) Loose Gen-Ba Knowledge Combination

There is a need for technology that loosely links Gen-Ba knowledge fragments, which are captured in the field through (A), with documents such as manuals of field operations. This loose structuring of Gen-Ba knowledge is necessary for utilization in internalization workshops (C). Here, we aim to extend the procedure-based and purpose-based knowledge graph [18,19], which has been developed and proven effective in caregiving and maintenance inspection fields. By leveraging generative AI technology, we will develop an interactive method to link field work processes and objects with Gen-Ba knowledge fragments using the knowledge graph. Loosely structured Gen-Ba knowledge fragments will be accumulated in a Gen-Ba knowledge database.

### (C) Automatic Recommendation in Internalization

There is a need for technology that supports efficient and effective collaborative symbol grounding (internalization) in workshops involving both skilled and unskilled participants, utilizing loosely structured Gen-Ba knowledge and LLMs and generative AI. Specifically, we aim to develop (1) automatic classification technology for Gen-Ba knowledge to make workshops more efficient, and (2) recommendation technology for Gen-Ba knowledge to make workshops more effective and stimulate discussions. Initial technology development and evaluation using LLMs have already been conducted [20, 21].

## 5 Illustrative Example: Greenhouse Farming

Using a specific example from the agricultural field in Japan [22], we explain the system based on the proposed concept. This example is a trial evaluation of the Smart Voice Messaging System conducted on greenhouse farming in Hokkaido in 2017. At that time, generative AI like ChatGPT was not readily available, and knowledge transfer was manually performed in the workshop using famer's voice messages and sensor information. Here, we describe a hypothetical scenario of how the proposed concept would be realized using generative AI, based on this example (Fig. 5).

### (A) Semi-automatic Aggregation in Externalization

During agricultural tasks, farmers' voice messages, photos, and physical sensor data (temperature, humidity, CO2 concentration, illuminance) are extracted as knowledge fragments. Farmers' voice messages record the tasks performed on the farm, know-how, thoughts, questions, notifications, and action items. Since voice messages, photos, and sensor data are recorded in a time series, it is desirable to consolidate related items into a single record. Therefore, generative AI is used to extract related voice messages and sensor data as knowledge fragments (Fig. 5 (A)).

### (B) Loose Gen-Ba Knowledge Combination

The knowledge fragments are linked to the following agricultural work structures (subject, process, location). Initially, the linkage is performed by generative AI and then verified by humans (Fig. 5 (B)). By linking to the structure, the subsequent search steps become more appropriate.

- **Subjects**: Vegetables (tomatoes, bell peppers), agricultural machinery, equipment, etc.
- **Processes**: Setup, sowing, fertilization, pesticides, growth inspection, harvesting, etc.
- **Locations**: Greenhouse numbers, warehouses, offices, etc.

### (C) Automatic Recommendation in Internalization

In internalization workshops, participants first select the knowledge fragment they wish to discuss. Then, multiple related knowledge fragments are extracted using generative AI (Fig. 5 (C)). Through the discussion of these related knowledge fragments, workshop members internalize the information by connecting it with their own experiential knowledge. In this process, text and data are linked to personal experiences, and symbol grounding occurs through empathetic discussions with other members. Additionally, Gen-Ba knowledge extracted by generative AI from the workshop discussions is accumulated in a Gen-Ba knowledge database.

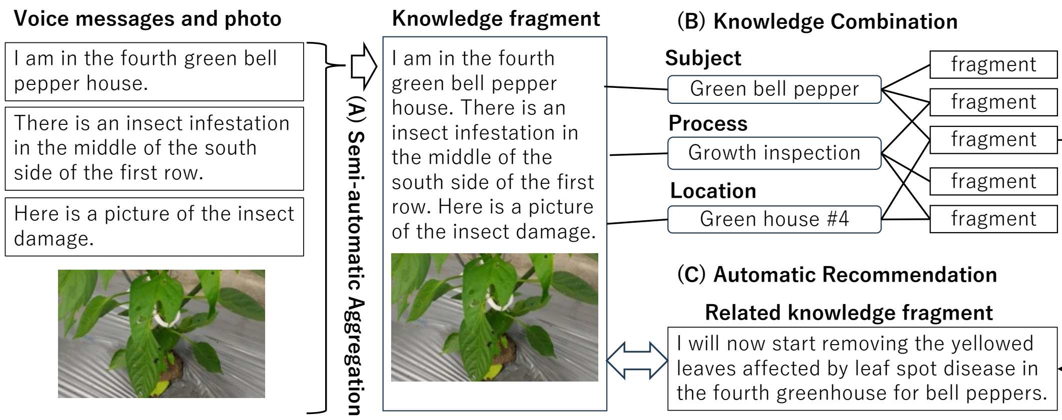


Figure 5: Illustrative Example in Greenhouse Farming

## 6 Discussion

### (1) Comparison with naive generative AI

Generative AI are inherently intelligent. In the proposed method, input data is consolidated as knowledge fragments, and the structure of tasks (subject, process, location) is incorporated. There is an alternative approach where input data is directly used as Retrieval-Augmented Generation (RAG) data, and relevant information is presented during internalization workshops without additional processing (B: loose Gen-Ba knowledge combination in Figure 4). In fact, additional processing can sometimes result in performance degradation compared to naive generative AI. However, it has been demonstrated that appropriate prompts can enhance the performance of generative AI [23], suggesting that suitable structures can be effective in improving generative AI. Determining what constitutes an appropriate structure remains a challenge for future research.

### (2) Collaborative symbol grounding

Humans acquire concepts and understand their meanings through verbalization. This verbalization does not need to be perfect, unlike mathematical proof. It may include situational dependencies and contradictions. Knowledge is internalized and becomes actionable when experiential meaning aligns with verbalized statements (symbol grounding). Traditionally, this process was conducted individually (Kolb's experiential learning model [24]). The proposed concept facilitates the internalization of knowledge not only through one's own verbalized experiences but also by empathetically sharing the verbalized experiences of other members in workshops. This can be referred to as “Collaborative Symbol Grounding.”

### (3) Comparison with the smart voice messaging system

The smart voice messaging system [16], which accumulates and utilizes voice messages, has been applied in various fields such as caregiving, agriculture, factories, ship engine rooms, maintenance, and inspection. It has been demonstrated that this system captures valuable knowledge that would otherwise be missed. In the caregiving field, trial evaluations confirmed that over 70% of valuable Gen-Ba knowledge were not recorded in the care record system [25]. The effectiveness of internalization workshops has also been demonstrated. However, these workshops require significant preparation effort and facilitation skills, making it difficult to operate sustainably them in the field. Research has been conducted to reduce preparation efforts and support workshop facilitations using LLMs [20, 21] including automatic preparation and recommendation, but the full utilization of generative AI remained as a challenge. This study addresses this challenge, aiming to establish sustainable internalization workshops in the field.

## 7 Conclusion

Generative AI is revolutionizing knowledge management, offering both unprecedented opportunities and notable challenges. Clarifying the potential and limitations of generative AI in this field holds significant research value. While its application in managing explicit knowledge is well explored, its role in handling latent and tacit knowledge remains underdeveloped and presents a critical challenge. This paper introduces the concept of the “Knowledge Digital Twin” as a model for managing Gen-Ba knowledge, including latent knowledge, and outlines the specific technologies required for its realization. Although Knowledge Digital Twin is currently at a conceptual stage, with implementation and evaluation as future challenges, this study provides a theoretical contribution by offering a promising direction for future knowledge management research in the era of generative AI.

## Acknowledgement

This work was supported by JSPS KAKENHI Grant Number JP22K05903.

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