Knowledge management in the age of generative artificial intelligence – from SECI to GRAI

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Abstract

Purpose – Generative Artificial Intelligence (GenAI) models are now able not only to recognize complex patterns from large amounts of input data but also to display them in context. This fact invites a critical analysis of the SECI model and its further applicability as an analytical framework for knowledge generation and transfer in organizations. This conceptual paper aims to take the SECI model with the individual SECI phases and analyze how GenAI changes the assumptions and descriptions of the original SECI framework. More specifically, the aim is to propose a revised SECI framework.

Design/methodology/approach – This paper aims to contribute to theory development of theories present in the literature. More specifically, it seeks to make a conceptual contribution that draws on one of the four types of conceptual contributions proposed by Deborah J. MacInnis, namely, envisioning, and is based on previous literature and the authors' thoughts and experiences to propose a revised SECI framework called GRAI, which stands for Generative Receptive Artificial Intelligence.

Findings – A better understanding of the further applicability of the SECI framework that arises with the introduction and application of GenAI models is not only relevant to the existing knowledge management (KM) theory but also to organizations. The proposed revised perspective of the SECI model, summarized in the GRAI framework, reflects the use of GenAI technologies in the corporate environment and thus allows the necessary stimulation of a discussion on how KM in general, and knowledge generation, in particular, will be affected and augmented by AI.

Originality/value – To the authors' knowledge, this paper is the first to systematically and comprehensively examine the established SECI framework and its wider applicability in terms of the potential impact of GenAI models on KM practices in organizations. The proposed GRAI framework is seen as a relevant contribution to the further development of KM theory.

Keywords Generative artificial intelligence, Knowledge management, SECI, AI, Knowledge generation, Knowledge creation, Knowledge transfer, GRAI

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1. Introduction

Generative AI (GenAI) is a subfield of Artificial Intelligence (AI) that subsumes systems or models that can generate new information based on the internal representation, which in turn was created using large amounts of suitable information as a source for an algorithmic training process, primarily using so-called transformer architectures, often based on the ground-breaking research of Vaswani *et al.* (2017) with their attention-based algorithm. García-Peñalvo and Vázquez-Ingelmo (2023, p. 14) define GenAI "[…] as the production of previously unseen synthetic content, in any form and to support any task, through generative modeling".

Recent developments in GenAI technologies have shown significant progress (Jarrahi *et al.*, 2022; Korzynski *et al.*, 2023), especially in the area of meaningful participation in human-driven dialog and the implicit representation of knowledge without explicit modeling. These developments open up a wide range of new applications, and for the first time in the development of IT-supported knowledge management (KM), there appears to be the possibility that GenAI may also be suitable for knowledge-intensive tasks that were previously reserved for humans (De Bem Machado *et al.*, 2022). GenAI models or technologies can recognize complex patterns from large amounts of input data and represent them in a contextualized way (Yan *et al.*, 2024). This offers machines a new way of representing and processing knowledge, a category of knowledge referred to as implicit or tacit knowledge in the field of KM.

The SECI framework proposed by Nonaka and Takeuchi (Nonaka, 1994, 2007) focuses on the knowledge creation process through the interactions between explicit and implicit/tacit knowledge. SECI describes four processes of knowledge creation in companies and emphasizes the interplay between tacit and explicit knowledge. It provides insight into how different types of knowledge can be created, converted and transferred with an iterative approach that is based on four phases that are Socialization, Externalization, Combination and Internalization. Despite the criticism, SECI has proven to be suitable for describing and understanding knowledge creation in organizations (Allal-Chérif and Makhlouf, 2016; Bandera *et al.*, 2017). The use of information and communications technology or technologies (ICT) in KM has always been seen as a high-potential application area from the SECI perspective (Sian Lee and Kelkar, 2013), but recent developments in ICT have significantly increased this potential. Therefore, it seems useful to explicitly examine SECI, i.e. the four phases of the SECI model, taking into account the dynamic developments related to the functions, capabilities, and limitations of GenAI, to see whether SECI should continue to be used as an analytical explanatory framework in this new era.

Against this background, this conceptual paper examines how the emergence of GenAI affects human-centered KM activities such as knowledge creation, knowledge sharing, knowledge use, and knowledge transfer. This research suggests that a revision of the SECI model is needed, as GenAI offers a new perspective on knowledge creation and transfer, shifting the focus away from pure human-centered interactions toward GenAI-augmented human-centered ones. This revised view is believed to provide new insights and knowledge to better understand how individuals engage in knowledge sharing and creation, especially of tacit knowledge in this still new environment. These new insights and findings could make a decisive contribution to theory development in KM when it comes to explaining the "machine-augmented" role of human actors in knowledge processes that are currently unfolding through the widespread use of GenAI. Therefore, this research uses the SECI model and its individual phases to analyze and reflect on whether and how GenAI changes the assumptions and descriptions of the original SECI. The result of this work– an earlier version of it was presented at the IFKAD conference 2024 in Madrid – is summarized in a revised SECI framework. This revised conceptual framework is called GRAI which stands for **G**enerative, **R**eceptive **A**rtificial **I**ntelligence and visualizes KM in the age of GenAI. GRAI is a relevant extension of the SECI model and its building blocks that takes into account an AI-driven environment from the beginning to explain and analyze KM processes, especially knowledge generation and knowledge sharing in organizations.

2. Methods

To achieve the aim of the paper and also to show that it meets the requirements of good scientific practice, this section explains the methodological approach used for developing the revised SECI framework.

As mentioned in the introduction, this paper aims to contribute to theory. More precisely, the present paper aims to contribute to theory development using one of the conceptual goals proposed by MacInnis (2011), namely "envisioning." At a more specific level, this contribution shall be made through "revising" something that has been identified before in a new way. Consequently, the present state of knowledge is identified (i.e. *see that the phenomena exist*) and then in the next step revised (i.e. *see phenomena that have been identified in a new way*; to reconfigure and shift them). In this paper, Jabareen (2009) is followed, this researcher understands a conceptual framework as an interpretative approach and not an approach that provides a causal or analytical explanation of reality. Thus, the authors of this paper view a conceptual framework as a means to promote understanding.

Within this research, a contextual review of previous research on the original SECI model was conducted. More specifically, the aim was to recapitulate the idea of the SECI model and the contributions of the individual components to the overall aim of the present paper.

This analysis was based on a wide range of peer-reviewed articles published in leading KM journals such as VINE *Journal of Information and Knowledge Management Systems* or *Journal of Knowledge Management*, or those journals that also published relevant papers on SECI. In the next step of the research process, the topic of AI was added to the analyses. More specifically, examples were identified that show how the individual SECI components could function with GenAI support. These examples were taken from the available literature on KM and AI. Additional examples were developed by the authors based on their many years of experience in teaching and researching KM.

Given the increasing availability and use of GenAI solutions and tools, this research is based on the argumentation that the integration of GenAI is an important and needed addition to the SECI framework. GRAI, the outcome of the work presented in this study and detailed in the subsequent sections, serves not only to demonstrate the further power of the SECI framework to explain knowledge creation and sharing but also represents a conceptual development of this framework through the representation of new interactions that result from the integration of GenAI into the knowledge processes. Therefore, it was necessary to develop a solid theoretical background based on the available literature on the SECI model.

3. The SECI model

The SECI model was developed by Nonaka and Takeuchi as a result of their studies on innovation in Japanese companies in the 1980s and 1990s (Nonaka, 1994, 2007). Hence, the model reflects the values and culture of Japanese business and work practices.

The model describes four processes of knowledge creation in companies and emphasizes the interplay between tacit and explicit knowledge. Knowledge is created through the conversion of implicit and explicit forms of knowledge (Hislop *et al.*, 2018). SECI provides insight into how knowledge can be created, converted and transferred with an iterative approach based on four phases of Socialization, Externalization, Combination and

Internalization, hence the abbreviation SECI. Knowledge creation in this model progresses through a spiral form rather than a circular movement (Nonaka, 2007). This is because knowledge moves up from the individual level to the group level and further (and finally) to the organizational level. Thus, knowledge is not only created by changing form but covers different levels of knowledge as well (Hislop *et al.*, 2018).

Knowledge in the SECI model refers to individual knowledge that is being possessed by and embodied within people. Consequently, information technology (IT) only plays a supporting role in most cases, as it was or could only be included to a limited extent in the language-based processes of knowledge creation and knowledge exchange. New knowledge in organizations is created through the SECI process that takes place in ba. Ba has been defined as a shared context in which knowledge is shared, created, and utilized (Nonaka *et al.*, 2000). According to Nonaka and Konno (1998, p. 40):

> […] ba can be thought of as a shared space for emerging relationships. This space can be physical (e.g., office, dispersed business space), virtual (e.g., e-mail, teleconference). mental (e.g., shared experiences, ideas, ideals) or any combination of them.

Consequently, context needs to be considered when trying to create meanings. Additionally, each mode of knowledge conversion calls for different types of knowledge, e.g. tropes, grammar and context, and non-verbal language such as body language.

Acknowledging that the application of GenAI can be multifaceted and is a rapidly evolving activity in which both the human actors and technology can participate (Böhm and Schedlberger, 2023), the focus of this paper is to examine the SECI model, i.e. the four phases, explicitly in the context of the functions and limitations of GenAI. While the SECI model has its limitations (Bandera *et al.*, 2017); its adaptable and practical character (c.f., Canonico *et al.*, 2020; Maras *et al.*, 2024) continue to make the model a widely adopted one.

In the following subsections, this paper will examine each of the phases in depth and explain how GenAI changes the assumptions and descriptions of the original SECI model.

3.1 Socialization

Socialization (S in the SECI model) refers to the exchange of knowledge between human beings. The main tools being used for encoding/decoding knowledge were and still are language and embodiment. Socialization can occur in groups of various sizes and with different forms of interactions (direct/mediated).

The socialization mode could be enhanced by GenAI in several ways. For example, virtual environments or platforms could be created where people in different (geographical) locations can interact in real time, fostering socialization regardless of physical distance. These platforms can simulate face-to-face interactions, enabling spontaneous exchanges of tacit knowledge. GenAI could also be used to analyze individual learning patterns and preferences and based on this personalized learning experiences tailored to each individual's needs could be designed (Sucena *et al.*, 2024). This insight would also support in selecting methods such as storytelling to facilitate socialization among people with similar preferences and needs. AI that is powered by advanced natural language processing (NLP) capabilities could also be used to analyze textual data, such as chat logs, emails or documents, to identify tacit knowledge embedded within conversations. By extracting implicit insights and facilitating context-aware recommendations, GenAI can promote socialization by connecting individuals with relevant expertise or facilitating discussions around shared interests. GenAI could augment the work of human mentors or coaches by offering additional personalized guidance, feedback and support that could be used for the work with individuals seeking to develop or deepen specific skills or knowledge areas (Sucena *et al.*, 2024). Through interactive dialogues and scenario-based simulations, AI mentors can facilitate socialization by encouraging reflective learning and collaborative problem-solving.

GenAI passively enables the participation of machines ("listening" to conversations, directly or using the digital traces) or in an active way ("participating" in a dialogue). Contrasting to earlier approaches, GenAI can participate in a socializing dialogue by "understanding" the conversation and the conversational context (also for longer dialogues and among different users) and taking an active role (replying in a more or less consistent manner) (Tang *et al.*, 2024). GenAI already can build an internal representation (during runtime) of the socialized knowledge and thus resemble the human way of understanding or will be able to do so soon. These adaptations will happen without explicit programming and thus represent a kind of emergent behavior when scaled over longer periods of continuous usage (Gabora and Bach, 2023). This is also related to Internalization (please refer to section 3.4).

3.2 Externalization

Externalization (E in the SECI model) represents the explication of (internalized) knowledge in some form of externalized information (codified knowledge). Commonly this process is used as a way to represent the knowledge independently from the bearer.

GenAI is expected to enhance the process of articulating tacit knowledge into explicit concepts, models or metaphors which can then be shared and communicated within the organization (Korzynski *et al.*, 2023). For instance, GenAI, which is equipped with Natural Language Generation (NLG) capabilities, can transform raw data, insights or tacit knowledge into coherent narratives, reports or documents to be used by organization members. GenAI can be utilized to extract meaningful patterns and generate structured representations that externalize tacit knowledge in a more understandable and communicable format. GenAI could also be used to create visual representations, infographics, or interactive data visualizations that encapsulate complex concepts or relationships. By doing so, tacit knowledge could be made more accessible and comprehensible to a wider audience within organizations. Furthermore, GenAI can assist in developing conceptual models, ontologies or taxonomies that capture the underlying structure and semantics of tacit knowledge domains (Schneider, 2024). GenAI can help identify conceptual patterns and relationships, supporting organizations to formalize and externalize tacit knowledge in a more systematic and standardized manner.

GenAI might be able to externalize upon request from the internal representation, but currently, it still fails to provide concise explanations or references. With this respect, there is a main difference to symbolic systems traditionally used in KM to represent externalized knowledge.

As a result, GenAI models cannot be examined in an analytic way like symbolic knowledge representations. The vast size of the models adds to the problem as well as the sub-symbolic representation of knowledge. These features generate challenges in terms of governance and explainability of GenAI models and machine learning models in general.

The current use of GenAI in chat-like applications such as ChatGPT and Microsoft CoPilot demonstrates that the technology can externalize knowledge for the human user in a way that is easier to consume as it can be "asked for" in a dialogue (aka, asking for suggestions/help instead of formulating a search query).

3.3 Combination

Combination (C in the SECI model) traditionally combines externalized knowledge (e.g. stored information in an IT system). This field could be supported by IT-system within the field of KM in substantial ways in the past by making large collections of information available (e.g. by integrating different information sources inside and outside of an organization), aggregating them and providing different forms of accessing the information (e.g. with search interfaces or visual representation of content topics), see (Wang, 2018). Analytic processes could extract information that was not explicitly represented in the information sources and provide new views and insight for the human user (e.g. by using data analytics technologies). The collaboration among humans also could be facilitated by ICT (Hijikata *et al.*, 2007).

GenAI provides a new way of accessing combined information (e.g. from the Internet, but also increasingly within the organizations) with a flexible dialogue interface (as opposed to access via search or direct access using a link). As a general pattern, combination as an activity is delegated from the human user to the GenAI, lessening the burden of doing it for the human user. Successful Large Language Models (LLM) in 2022 initially focused on the use of available Internet sources (e.g. in the ChatGPT application starting from version 3) that have been collected up to a certain point in time, representing a more generic combination of externalized knowledge (also called foundational models). More recent models allow the augmentation of the foundation models by on-demand information acquisition tasks to reflect a more dynamic update of the information combination. An "action component" (using plugins or application programming interfaces (API)) provides ways to embody action on knowledge-intensive activities, e.g. when the existing internal knowledge need to be augmented by external information sources (e.g. for fact-checking or obtaining current data (whether company information, stock rates, etc.). Also, the adaptation of a foundation model to a more specific domain is possible with a model adaptation called fine-tuning, carried out with specific documents from that domain, e.g. from an enterprise repository. Finally, the combination of traditional retrieval functionality with the new abilities of GenAI is increasingly being used, employing the concept of Retrieval Augmented Generation (RAG), see Zhao *et al.* (2024), with enterprise solutions emerging from various vendors, e.g. Oracle (2024) and Elastic (2024). Besides combining technologies from two different worlds, providers also aim to offer enterprise-grade foundational models to counteract the problem of bias (Soul and Bergmann, 2024).

On the other side, there is also the danger that, over time, human users lose the ability to combine information on their own when they rely too much on the abilities of GenAI as described above. Another layer of abstraction is added to the task of combining human knowledge, providing more efficiency and comfort on the one side but also less transparency and traceability on the other side. These advanced knowledge combination abilities are still limited and not as universal as those of a human knowledge worker, but are expected to increase over time.

The two main differences between the earlier functionalities in IT-based Knowledge Management and the new possibilities using GenAI technologies are (a) the common-sense knowledge that is represented within the models, which makes it easier to understand the user request and to encode the combined information in the format that the user asks for (taking into account nuanced aspects like format, language, tone and more) (Zhao *et al.*, 2023). Secondly (b) the concept of context that is used during the conversation setting with the user helps to resolve homonyms and other tricky language specific features to increase the understanding of the knowledge demand of the human user (Grindrod, 2024). The embedding in an explicit dialogue setting further allows the human user to make specific references to earlier requests or generated information, allowing for iteratively shaping the combined knowledge in a very natural way without requiring expert knowledge to use the system effectively, as (Iga *et al.*, 2024) describe in their application to enhance hypothesis discovery creation.

3.4 Internalization

Internalization (I in the SECI model): is the process of consuming information (externalized knowledge) into an internal representation that the human user can act upon after it has been internalized. This process could also be considered as the "understanding" of externally represented information. From a human perspective, it is also similar to the learning process with providing instruction materials (Hoe, 2006). The difference to socialization is the passive role of the information compared to the active interaction among the participants in a socialization process. Internalization, therefore, depends on the absorption capabilities and the relevant prior knowledge of the human user.

Traditionally IT systems were only partially successful within this field and required massive (knowledge) engineering activities, even for limited domains. GenAI has reached significant advancement (a breakthrough) here as the internalization does not need these engineering efforts anymore for explicit knowledge representation. Although the training efforts are still massive (for model building and dialogue training) for the base models, they scale much better as the processes are almost fully automated. This can be verified by the fast development of new base models on a constant basis. Model adaptation during run-time already become available and with this feature, the lifetime of such models has the potential to become more universal and composable, e.g. chaining of several LLMs with different objectives and tasks (Wu *et al.*, 2022). Specialization and lifetime learning could be a future option.

The internalization abilities of GenAI technologies can be seen as the enabling feature for self-directed learning and development, especially if it comes to the participation in the dialogue with other agents, whether they be human users or other machines. The internalization capabilities of LMM focused on textual sources first but also became multimodal, enabling the internalization of images and video sources. Besides, GenAI can be trained for domain-specific information types, such as source code for software development, for example. First applications of such a participatory latent observation process of the machine as a passive actor with the intention of continuously building an internalization of the user's interaction with his or her personal computer is the Microsoft Recall feature for the Windows 11 Operating Systems (Computerworld, 2024). From the perspective of this research, the discussion on the usefulness of the feature and the possible benefits is interesting with respect to technology adoption and the right balance between privacy concerns and the requirements of control over the conversation and participation of the machine. In this sense, it mimics the characteristics of human communication and knowledge exchange processes in which humans and organizations alike stress the importance of carefully selecting their communication partners and like to keep control over what information to share. Human and machine interaction in the context of the SECI components needs to pay respect to this feature in terms of transparency when being present or absent in the discourse to build trust in GRAI systems (Barman *et al.*, 2024).

GenAI systems are expected to improve their Internalization capabilities even further in terms of timeliness, effectiveness and universality, and this ability can be understood as the enabling sector within the SECI model as it can be seen as a prerequisite for the (almost) autonomous knowledge creation for machines and the proactive participation in the human knowledge exchange.

4. SECI in the context of generative AI – the GRAI framework

Within the field of KM, the SECI framework could often be used as an explanatory model for the transformation processes related to knowledge within an organization or group. This research underlines the continued explanatory power of SECI for the creation and transfer of knowledge, taking into account the functionalities of the new technologies and the more active role of the machine in knowledge creation processes. It proposes an extension of the original model to reflect that IT technology requires a new level of active integration. This, in turn, is expected to lead to a new quality and quantity of support functions, which could be explained using the developed framework.

There is already some related research that aims toward a similar direction. For example, Lee and Park (2023) investigated the relation between AI and human actors with a focus on the different forms of interactions. Although they took the SECI model into account, they did not specifically study the use of generative technologies in the different phases of the model. The work of Jarrahi *et al.* (2022) addresses the relationship between human actors and AI technologies with respect to different phases in the KM process but without explicit reference to the SECI model, while the research of Joshi and Sinha (2023) focuses on the aspect of knowledge creation with reference to the SECI model. Against the background of ongoing developments, there is a great need for new or adapted explanatory models and the authors of this paper are convinced that a revisited SECI model can provide an important contribution in this direction.

4.1 The GRAI framework

A revised SECI model should take the machine as a participant into account that can play an active or a passive role. The active role would generate an output or a response, while the passive role could be compared to listening and adapting/rebuilding the internal (knowledge) representation. Consequently, the four areas would each be split into a human perspective and a machine perspective, leading to eight fields of action in the new model, as shown in Figure 1. The final outcome is the GRAI framework, which stands for **G**enerative, **R**eceptive

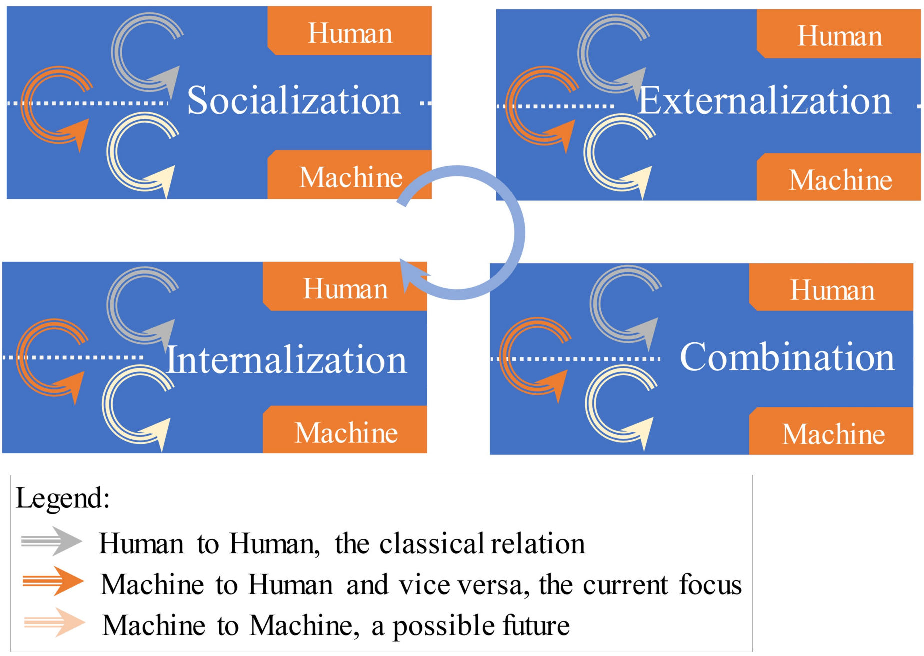

Figure 1. GRAI – Extension of the original SECI model with an additional agent layer (human/machine) and the respective fields of interaction between them

Source(s): By authors

Artificial **I**ntelligence, and presents a proposal of an updated model that takes into account recent developments regarding GenAI and its consequences for KM.

Sticking to the original knowledge conversion cycle from Socialization to Externalization to Combination and finally to Internalization, GRAI opens up for a number of new relations besides the classical ones that always assumed the human-to-human relation. The new relations are denoted with an appropriate subscript on the respective field of the SECI model (‘h’ for human, ‘m’ for machine), e.g. for all the traditional elements and conversions that have been studied extensively: S_h, E_h, C_h and I_h. The situation in which those knowledge exchanges are completely left to the machine(s) can be considered as a topic for future developments and investigation, although first experiments toward this direction are already appearing, e.g. Sukhbaatar *et al.* (2024). This would be represented by S_m, E_m, C_m and I_m.

In the current development stage of GenAI the most interesting fields are those in which humans and machines interact with each other between the different stages. This leads to a combination of two actors (human and machine) within two role positions in the four fields of the original SECI model. The resulting eight different interaction fields are briefly described in Table 1 to illustrate the different interactions patterns between the human user and the GenAI in the machine role.

Since the machine as an actor in knowledge creation and knowledge use is new in this form, it becomes important to study this new and emerging relation with the human users as it is very likely that the presence of the machine is going to change the way how knowledge is being created and used. These so-called interaction fields are explored in more detail in the following subsections.

The addition of the machine as an actor in knowledge creation processes does not mean that the authors of this paper understand both roles as equal. However, they see dominance or importance of the human user in this process, which is still seen as “human-centered” (the human actor gives the decisive steering impulse) and/or “machine augmented” (the machine actor complements or augments the actions of the human actor

Table 1. Overview on the different interaction fields between human and machine in GRAI

Interaction field	Short description
$S_m \rightarrow S_h$	A dialogue-oriented setting that is oriented toward knowledge or information acquisition for a human user
$S_h \rightarrow S_m$	Another dialog-oriented situation with the focus on specifying a complex information demand or situation, incl. instructing the GenAI
$E_h \rightarrow E_m$	The situation in which the human user adds additional relevant materials into the conversation, providing specific contexts
$E_m \rightarrow E_h$	The generation of content from existing unstructured inputs with a predefined structure or attributes
$C_m \rightarrow C_h$	The generation of complex summaries on a subject or provided information sources for a specific information demand or given style
$C_h \rightarrow C_m$	The human user combining different subjects in a dialogue, requiring the machine to combine pattern that are unlikely to appear together

Source(s): By authors

in a complex, consistent and context-related way). Depending on the intensity of the support and the actor that takes the assistance role, a distinction could be made between human-in-the-loop (a human actor being assisted by a machine) or machine-in-the-loop (a machine assisted by a human). In the interaction fields of GRAI both situations could arise. The way how these relations will influence each other is also investigated by (Yang *et al.*, 2023).

The application of these concepts will vary, because currently GenAI technologies are resource intensive (from a computational point of view) and costly (even when used as cloud services). This could lead to a slower adoption in SME compared to larger organizations, but on the other hand SME could also take a lead in technology adoption if the use of GenAI provides them with a competitive edge in their knowledge processes that they could not achieve otherwise, e.g. because their human resources are limited. Over time the resource intensity will become a lower barrier due to technology development and competition in the emerging market of GenAI providers.

4.2 The socialization interaction field in GRAI

Socialization is a dialogue-oriented setting with the primary intention of knowledge sharing between two actors, including the comprehension of other viewpoints and opinions. It is a highly contextualized process that is transmitted using natural language.

From the perspective of the machine toward the human agent, ($S_m \rightarrow S_h$) it can be seen as a setting that is oriented toward knowledge or information acquisition for a human user, e.g. explaining a topic to a human user. This might be an interactive information research context to generate (new) knowledge. The socialization aspect here is generated by a continuous dialogue that can take the context of previous exchanges into context and hence mimics an understanding of the human user (e.g. concerning the level or detail or complexity) in a much more human fashion than a classical information retrieval task. This interaction field might have some similarities to $I_m \rightarrow I_h$, which is discussed in section 4.4.

The socialization interaction from the human agent to the machine agent ($S_h \rightarrow S_m$) is another dialog-oriented situation with the focus on specifying a complex information demand or situation, e.g. in an extensive and possibly iterative prompting interaction that informs about a situation (e.g. providing a richer context for the dialogue). Currently, this is usually used with the intent to generate something, but possibly also to explain a certain part of the real world to a GenAI ("instructing"). This situation typically bridges the world of the human user to the perception of GenAI, which is separated from the reality and reconstructs this reality indirectly from the artifacts in the digital domain.

4.3 The externalization interaction field in GRAI

Within the externalization interaction field, the main focus is the connection between the internal knowledge representation models and the physical and digital reality with the data and information coming from there. This transition process usually requires substantial efforts to integrate new information into existing models or to make information accessible for those models. This aspect refers to human users and IT systems (machine agents) that should deal with new information that is often contextualized and vague/inconsistent. GenAI offers new capabilities to bridge this gap in a more efficient way (without the need to build specific IT solutions) and in a more effective way (being able to work with vague/inconsistent information due to the contextualized information processing capabilities of LLMs).

More recent versions of LLM-based systems such as OpenAI ChatGPT or Google Gemini allow the human user to add additional relevant materials into the conversation, e.g. using the "memory function" of those systems. This enlargement of the context relates to the interaction field $E_h \rightarrow E_m$ as it helps the machine to identify a more precise context with a domain specific focus in the dialogue. This way a general conversation can be leveraged toward a specific direction by the human user by providing externalized information to the machine. Another application use case that is emerging rather frequently here is the use of GenAI in retrieval-oriented task using Retrieval Augmented Generation (RAG), which combines an initial search query with specific document collections (externalized information) to derive a more specific search results when the original query is augmented by the generated content from the externalized information (Yu *et al.*, 2024). Contrasting to the use-case of information retrieval in enterprise specific information sources (enterprise search), in the field of KM, the use of GenAI could introduce a bias in the results that was originating from the foundation models used. However, these effects might be similar to the contextual integration of a human user and could be counteracted with carefully selecting and adopting the right foundation model.

Another interesting interaction field is $E_m \rightarrow E_h$ where the generation of structured content from existing unstructured information that contains this information only in an implicit form, e.g. the extraction of product data aspects in a structures tabular form a set of product images. Here the structured product attributes are encoded in the image of the product (e.g. color, material) and while human users usually recognize these attributes easily and with high precision, machines often failed in recognizing those aspects equally well. GenAI with multimodal capabilities can use the recognition functions for objects and their attributes and generate structure product information in a table-like structure. The results could then be used for product catalogs, e.g. in the e-commerce domain.

4.4 The internalization interaction field in GRAI

Internalization relates strongly to the creation of internal models (or representations) of the knowledge of the outer world of the agent reflecting the views and beliefs of the agent. The assistance by GenAI might both help the internalization processes of the human agent but might also be beneficial to proactively build or adapt (digital) representations for the machine agent.

The direction from the machine agent toward the human agent ($I_m \rightarrow I_h$) is the process of supporting the internalization of a human user with the help of GenAI, e.g. creating a better understanding on a certain concept or topic. In contrast to the somewhat similar to interaction field $S_m \rightarrow S_h$ the aspect of human learning is more prominent in this situation as the internal knowledge representation of the user is changed, whereas in the Socialization Interaction Field the information or knowledge provision is in the main focus.

The opposite direction ($I_h \rightarrow I_m$) is a situation in which the GenAI has an observing role for a longer period of time to suggest appropriate support actions for the human user based on the internal model built from those observations. Such situations could be a moderating role during Online-Meetings (including summarization and analytics of the discourse) or the general user support across different applications, e.g. the Co-Pilot-functionality in Microsoft Office 365 products.

4.5 The combination interaction field in GRAI

The interaction field of combination might have gotten the most attention with the advent of GenAI systems as the way that LLMs could generate content that was combined from a large source of data was unique with the advent of the ChatGPT-system as it did not require specific expertise to access this functionality – quite contrary requests for the combination of externalized information could be stated in natural language with all its ambiguity. With respect to the interaction field $C_m \rightarrow C_h$ the generation of complex summaries on a subject or provided information sources was one of the most prominent examples. The combination task could be configured for a specific information demand, given style, or tone of text (e.g. content generation for a specific target group) to be used by the human agent for further processing. Another example in this interaction field could be the generation of meeting protocols from the transcripts of Online-Meetings, which also relates to $I_h \rightarrow I_m$.

Likewise, the flexibility of combining content elements in very different ways could also be used as a creativity tool for the human user ($C_h \rightarrow C_m$). Here, the human user combines different subjects in a single prompting request or dialogue sequence and therefore requires the GenAI-system to combine different patterns that are otherwise unlikely to appear in the existing reality, e.g. the generation of images in the style of a certain artist or imagery that combine aspects that are not existent in the physical reality (e.g. the generated images of the Pope in a white down jacket). The interesting features in this kind of combination is the level of abstraction that is being achieved when combining different concepts to create something new (e.g. the specific aspects of a down jacket with the individual characteristics of the Pope).

The observations in the eight communicative settings depicted above demonstrate that the new role of the machine using GenAI is changing the way IT-supported knowledge management (especially knowledge conversion) works. They also reveal that the SECI model, augmented with role separation between human and machine, adds another relevant dimension to the model. This extension can be used to explore the new observations and experiences that are made by experimenting with and using of the GenAI technology.

5. Conclusion

This paper assumes that the SECI model, despite its weaknesses, provides a good analytical framework to describe and investigate knowledge generation and transfer in organizational settings. GenAI offers new opportunities and challenges for KM in general and the SECI model and its further usability.

Based on a conceptual approach to theory development, the GRAI model is proposed, a revised version of the SECI model. GRAI considers GenAI-related observations and technology use and discusses the implications for the field of KM. Since the underlying technology of GenAI possesses advanced functions to understand and follow a dialogue (from a linguistic and semantic perspective) and represents common sense knowledge as background information, it becomes feasible for GenAI to participate in a meaningful dialogue with human actors. This paper reflects these developments from a KM perspective and based on that provide the GRAI framework that is aligned to the SECI model and intended to understand the current developments better.

Working on GenAI from the perspective of KM currently feels good and bad at the same time: the *bad feelings* come from the observation that the engineering of GenAI systems mainly focuses on the area of building or deriving systems by (customized) training data or the research on new algorithms, which are often black-boxes from the level of application and explanation. Likewise, the field is developing at a high pace, leaving only little time for studying the effects, especially from the perspective of knowledge-intensive activities with the human in the loop. The *good feelings* come from the perspective that this research tries to look beyond the current technical developments in the sense that we consider the participation of the machine in the human (knowledge) interaction. This leads to the fact that the input becomes more contextualized, includes more (implicit) feedback, and is more human as it covers the human way of (co)creating knowledge and exchanging knowledge. This idea of cocreation might also be central for the thinking about the GRAI leading to a model of coevolution, beneficial for the human user and the machine alike (Böhm and Schedlberger, 2023). As this cocreational collaboration between man and machine continues to evolve, more balanced views of good and bad feelings can be expected, ultimately leading to a sense of confidence on how to use GenAI and to what extent or purpose. This will also relate to a continuous *trust building* toward GenAI that results from positive user experiences on the human side. As the trust toward these relatively new technologies builds up over time, legitimate confidence in the technology is strengthened and competence attained on using the tools in the right way.

Being a conceptual paper, the authors are aware that the study has limitations. GRAI should be tested in different organizational and cultural contexts. The role of context in general and in relation to KM is well known (Augier *et al.*, 2001; Weir and Hutchings, 2005). It is known that some people (cultures) are more willing to share their knowledge than other cultures. Against the background of a new actor (the machine) in the knowledge generation process, there is a need for studies that investigate how people react to this new actor. Do they accept this actor? Always? And if not, when is it allowed to be there, and when it is not?

In sum, this research introduces the GRAI framework that provides a novel perspective that allows new ways of discussing KM activities in organizations in the age of machine-augmented knowledge processes that deal with contextualized implicit and explicit knowledge.

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