Managing Human and Artificial Knowledge Bearers

The Creation of a Symbiotic Knowledge Management Approach

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Abstract. As part of the digitization, the role of artificial systems as new actors in knowledge-intensive processes requires to recognize them as a new form of knowledge bearers side by side with traditional knowledge bearers, such as individuals, groups, organizations. By now, artificial intelligence (AI) methods were used in knowledge management (KM) for knowledge discovery, for the reinterpreting of information, and recent works focus on the studying of different AI technologies implementation for knowledge management, like big data, ontology-based methods and intelligent agents [1]. However, a lack of holistic management approach is present, that considers artificial systems as knowledge bearers. The paper therefore designs a new kind of KM approach, that integrates the technical level of knowledge and manifests as Neuronal KM (NKM). Superimposing traditional KM approaches with the NKM, the Symbiotic Knowledge Management (SKM) is conceptualized furthermore, so that human as well as artificial kinds of knowledge bearers can be managed as symbiosis. First use cases demonstrate the new KM, NKM and SKM approaches in a proof-of-concept and exemplify their differences.

Keywords: Knowledge Management, Artificial Intelligence, Neuronal Systems, Design of Knowledge-Driven Systems, Symbiotic System Design.

1 Introduction

Being faced with the role of new technical and digital actors and knowledge bearers, such as Artificial Intelligence (AI)-based systems, the danger is present, that artificial systems are evolving and generate knowledge, that is undesired from the viewpoint of an organization. An example refers to the generation of selling recommendations: Although these might perform well on training and test data sets, they disregard the human's knowledge need in its business process context. Further, humans might reject AI-based insights, because they cannot reason for the system's plausibility and its conformance with organizational objectives.

Inadvertence towards the management of knowledge of all kinds of knowledge bearers can hold enormous risks. For instance, one cannot identify if the system focuses on wrong influence factors and one blindly must follow its recommendations. However, the compelling necessity for an instrument becomes transparent that enables the prevention of undesired knowledge bases of an organization. This includes human-based knowledge bases as well as technical knowledge bases of individual machines.

Although being faced with numerous AI method uses in KM, such as for knowledge discovery, the reinterpreting of information, and the implementation for KM, like big data, ontology-based methods and intelligent agents [1], the joint management of human and technical knowledge bearers has not been issued so far. This is supplemented by contemporary attempts to develop AI-based systems. Since these focus on the learning task specified, neither the manageable development of AI-based systems, which is with regard to objectives of an organization, nor the management of knowledge generated by AI-based systems have been issued, yet.

If it was possible to systematically and efficiently guide the evolution of an organization's joint knowledge bases, so namely human knowledge bases as well as artificial knowledge bases, the trustworthy and ethical justifiable use of AI-based systems is supported. So, the following research will focus on the optimization of knowledge bases with the intention to answer the following research question: "How can machine-based knowledge and human-based knowledge be managed efficiently in an integrated way?" Sub-research questions addressed are:

1. "How can AI-based systems be considered as knowledge bearers, so that traditional KM is enhanced?"
2. "How can human knowledge be considered at knowledge-driven enterprise information systems, so that dealing with AI-based systems is enhanced?"

This paper contributes with a new kind of KM approach, that enables the symbiotic management of technical and human knowledge bases. Since the approach proposed intends to enable the traditional KM by knowledge from artificial knowledge bearers, throughout the paper, the linking with traditional KM will be regarded. The focus is set on how human-based knowledge can be managed more efficiently (first sub-research question). For instance, the approach will enable the question how the knowledge need of a professional buyer having a need for market analyses and the knowledge supply of an ANN system about the prediction of market prices can be allocated efficiently.

Further, the symbiotic management approach proposed intends to enable the dealing with AI-based systems, by knowledge from human knowledge bearers. Since this must be compatible with traditional KM activities, throughout the paper, the reinterpretation of KM activities in ANN context is regarded. So, the manageable development of AI-based systems will be enabled. Further, new kinds of KM roles and management levels have been derived and the focus is set on how machine-based knowledge can be managed efficiently (second sub-research question).

The research approach is intended to be design-oriented as Peffers proposes [2] and the structuring of this paper is derived from the Design-Science-Research Methodology (DSRM) as follows: The second section provides a theoretical foundation and underlying concepts. The third section presents a methodological required specification for the management of knowledge bearers: requirements are derived, which are separated from the design of required artifacts. So, they can function as quality gates for artifacts in the fourth section. Here, the Symbiotic Knowledge Management (SKM approach) is set up that considers a KM and the novel Neuronal Knowledge Management (NKM). The fifth section demonstrates the application in case studies, so that the requirement fulfillment can be evaluated (sixth section). The final section concludes the paper and presents implications for a contemporary management of knowledge and enhanced ANN system development.

2 Background of Managing Knowledge

Underlying concepts for the research presented here refer to the definition of knowledge (first sub-section) and the domain of KM (second sub-section). As ANN systems are considered as technological knowledge bearer manifestation, relevant concepts of the domain of ANN are presented in a third sub-section. As both kinds of knowledge bearers are evolving over time, contemporary insights of a knowledge development are considered in the fourth sub-section. The literature review is issued finally.

2.1 Theoretical Foundation

Knowledge Attempts to define the term knowledge can be traced back to ancient times. Inter alia, attempts for definitions can be found in the following.

- *Everyday understandings* recognize knowledge as an awareness of something [3, 4], which results because of family resemblances among items to be aware of [5, 6].
- *Philosophical definitions* focus on the nature of knowledge as an insight from an epistemological perspective. It therefore has to stand different levels of justification [7, 8].
- *Educational contexts* consider knowledge to be a concept of competences enabling individuals to act in specific situations [9, 10].
- *Pedagogical and cognitive-psychological definitions* consider knowledge to be a fluent information schemata being perceived by a person and integrated in the person's long-term memory [11, 12]
- *KM- and Knowledge-Logistic-oriented approaches* recognize knowledge as the unity of skills, cognition and capabilities, which are used for the solution of problems [13, 14]. So, knowledge has a contextual meaning, dynamic nature, tacit dimension, is socially constructed [15], and it can be used in order to realize a competitive advantage [16].
- *Information-System-oriented and AI-based definitions* recognize knowledge to be information, which is valuable in specific situations and supports the identification of decisions [17]. Issuing the distinction of data, information and knowledge, definitions focus on the interlinking and organization of information.
- *Neuro-Scientific and Cognitive-Scientific attempts* recognize knowledge as information stored, integrated and organized inside the brain [18]. So, by the act of selecting, comparing, evaluating and drawing consequences, knowledge is made from the resource of information [19].

As the SKM approach intends to integrate the traditional KM and AI system development, and the identification of knowledge within neuronal structures is intended, an adequate definition of knowledge must bring together aspects form a non-machine side inspired by the KM domain (everyday, philosophical, pedagogical and knowledge management contexts, etc.) as well as aspects from a machine side inspired by the AI domain (information system, machine learning contexts), so that a knowledge definition supports the everyday understanding about knowledge-related concepts and can stand as a foundation for knowledge objects to be managed.

Knowledge Management The knowledge management (KM) deals with the creating, sharing, using and managing of knowledge and information of an organization [20]. Principally, there are two kinds of KM [15, 21–27]:

- *Resource-oriented KM*, which focus on the management of knowledge as resource, so that knowledge is recognized to be administrated.
- *Process-oriented KM*, which focus on the utilization of knowledge. It appreciates knowledge to have a value and to be part of the entire value chain of a company.

Concrete KM models and concepts e.g. refer to [15, 28–31]. Although not any KM model addresses a machine-based knowledge, the Potsdam KM model [15] is attractive to stand as a foundation for the conceptualization of SKM approach in particular, as it provides an ordering system, which is based on the dimensions of the following three: (1) the organizational range providing a foundation of traditional knowledge bearers, (2) the procedural range providing a foundation of by knowledge traditionally affected areas, and (3) the personnel range providing a foundation of traditional KM stakeholders. Further, the Business-Process-Oriented KM model (BPO-KM, [15, 30, 31]) is attractive to stand as a foundation since it provides valuable framework conditions.

Artificial Knowledge Bearers Having a long history, the origin of Artificial Intelligence (AI) is typically dated back to the 1950 [32]. Often, it is differentiated by the degree of intelligence [33, 34]:

- *Narrow AI* focuses on the automation of a precisely defined task. Here, knowledge refers to a limited set of capabilities.
- *General AI* addresses systems having the physical and intellectual capabilities of a human person. Here, knowledge refers to a circumstantial and complex set of capabilities.
- *Super AI* issues systems that are much more intelligent than humans. Here, knowledge refers to the most complex and ambitious set of capabilities.

Further, the AI is differentiated by its interpretability, which centers symbols [34, 35]:

- *Symbolic AI* tries to capture a certain knowledge domain by explicit symbols. As these traditionally are coming from the human model creator, the intelligent performance of a system is realized on behalf of a top-down approach and with the aid of symbols of a conceptual level. Hence, its interpretability is not an issue. Often it is referenced orthodox AI or as GOFAI (Good-Old-Fashioned AI). Here, one can argue to deal with explicit knowledge.
- *Neuronal AI* tries to capture a certain domain of knowledge with the aid of data. Hence, it rather refers to a bottom-up approach, which is enabled by an as precisely rebuilding of the human brain as possible. Here, the system behavior is difficult to interpret since knowledge is not explicitly constituted by symbols and one can argue to deal with tacit knowledge.
- *Symbolic Distributed AI* tries to combine the first two kinds of AI, as it recognizes the symbolic nature of knowledge and considers a distributed processing. Here, one can argue to deal with both explicit and tacit knowledge.

So far, the issue with AI-based systems, such as ANN, refers to the fact that no explicit, human understandable model is created [36, p. 136]. Its learning and so the structure building of a knowledge generation entirely builds on the optimization of thousands weights and floating point parameters. Implicitly, they function as tacit knowledge. Principally, this limits the capability of the SKM approach by now, as only knowledge from a symbolic AI can be issued. However, the interpretability of neuronal AI systems, such as ANN, is improving and these may not be excluded from an organization-wide management of knowledge.

Since AI-based systems operate on base of the generation of floating point parameters, the very atomic neuronal activity is considered to be a foundation for the SKM approach. Building on neuronal activations, that hold floating point parameters, knowledge can be considered as a neuronal pattern. This refers to a current, evolves over a certain period of time and causes a specific behavior of consecutive neurons [37]. As the smallest denominator of a knowledge definition, the SKM approach will be based on this knowledge understanding. Following a constructivist approach, here, the assumption is implemented, that each neuronal knowledge object is considered as an activation-based, codified form of knowledge that is considered with sooner or later complexity levels as clearly recognizable knowledge from the perspective of KM and everyday understandings.

Knowledge Development As contemporary pedagogical and cognitive-psychological approaches assume knowledge to be combined successively to more complex schemata and by this, a knowledge structure evolves over time [12], the learning and the development of knowledge is realized phase-wise and needs to be supported (e.g by pedagogical valuable designs):

- In the first phase, knowledge is prepared to be crystallized by *fluid systems*, such as the phonological loop, episodic buffer, visuo-spatial sketch pad and the central executive [38–40]. As these deal with schemata individually, different kinds of individual capacities and learning barriers need to be addressed, so that they do not overload the working memory in the sense of the cognitive-load theory [41,42]. This goes along with the respecting of individual emotional factors of human learners [43].
- In the second phase, knowledge is anchored within the crystallized knowledge base, e.g. by repetition. So, the volatile knowledge constructed by fluid systems is stored sustainably in the long-term memory, which therefore is called *crystallized system* [44].

Regarding to the current focus of a learning phase, each schemata demands for an individual support of pedagogic designs. These are valuable for the symbiotic KM because of the appropriate addressing of learning characteristics. By the realization of activities with the aid of pedagogic designs, the efficient guiding of a human or machine-based learner is enabled. Therefore, an adequate management of knowledge, which intends to systematically evolve an organizational knowledge base, needs to address the knowledge development with regard to the following three: first, the individual knowledge bearer, second, the schemata and third, the learning phase.

2.2 Literature Review

Alavi and Leidner have reviewed KM literature. They identified detailed processes and the role of information systems [45]. Weinreich and Groher reviewed contemporary KM activities and they identified architectures for the efficient capturing of KM activities [46]. On base of a great collection of KM activities, well documented KM processes and information systems, one can recognize the KM as foundation for the efficient management of human knowledge bearers.

Tsui et al. reviewed the roles of AI in KM. They argue if AI systems are ready to converse with humans [47] - from this perspective, they won't demand for management. Liao reviewed KM technologies and AI applications and identified an integration of qualitative and quantitative methods at that time [48]. Having reviewed recent attempts of AI methods and KM systems, Begler and Gavrilova identified AI methods as tools simplifying isolated KM activities [1]. A management approach recognizing AI-based systems as knowledge bearers, which need to be managed, has not been issued, yet. Also, a holistic approach for the common management of human and artificial knowledge bearers is not present.

Although Tsui et al. have reviewed KM approaches, they argue if KM is a brand name of knowledge engineering. Being dominated by computer scientists and AI researchers in particular, the construction of intelligent agents and ontologies is issued [47]. Neither an integration of AI-based knowledge with the organizational knowledge base nor the controlled or educative knowledge building is present. The AI system development rather focuses on the performance-oriented training and generalization [49]. So, the organization's holistic objectives - these go beyond the limited context of a specific learning task - are disregarded. Further, contemporary approaches lack at the identification of a common understanding of knowledge, that is in the sense of traditional KM and corresponds to AI-based systems.

In contrast to the above work, this contribution specifically focuses on the joint management of human and artificial knowledge bearers. Synthesizing existing models, in the sense of a holistic framework, an approach is presented, that identifies a joint understanding of knowledge as well as its management with regard to organizational objectives.

3 Requirements for the Management of Knowledge Bearers

In accordance with Design-Science oriented research [2], requirements are defined before the artifacts are conceptualized. Since these will serve as design maxims for the SKM approach set up, they issue the following: First, the SKM approach will be based on contemporary research presented in section 2.1. Second, the SKM approach will progress the state-of-the-art presented in section 2.2. Third, they support the comparability of subsequent research. Having set up these requirements in a workshop session, these were confirmed by three experts from the field of KM, business process management and ANN construction each. Tab. 1 presents an overview.

Table 1: Requirements for the Management of Knowledge Bearers.

Req.	Description
1.	The SKM approach needs to stand as management approach for the following three kinds of combinations: first, organizational knowledge only (cf. knowledge at section 2.1), second, neuronal knowledge only (cf. artificial knowledge bearers at section 2.1), and third, both kinds of knowledge jointly.
2.	The SKM approach needs to reflect contemporary ontological dimensions. This requirement recognizes knowledge to be constructed on traditional ontological levels (cf. KM at section 2.1) and includes AI-based knowledge bearers (cf. artificial knowledge bearers at section 2.1).
3.	The SKM approach needs to reflect the educative dimension of knowledge bearers (cf. knowledge development at section 2.1). Here, human as well as machine-based knowledge bearers are faced with limited capacities, learning burdens, emotional factors, and different kinds of memories. This requirement issues the efficient knowledge development.
4.	The SKM approach needs to reflect different kinds of stakeholders because the dealing with human and technical knowledge bearers demands for different competences. While some experts are coming from the process domain and deal with KM issues (cf. KM at section 2.1), others are coming form the ANN domain and deal with the construction of AI-based systems (cf. artificial knowledge bearers at section 2.1).
5.	The SKM approach needs to reflect the contemporary procedural range. This recognizes knowledge to be constructed on different procedural levels (cf. process-oriented KM at section 2.1). For instance, this refers to the biological plausible knowledge processing of ANN and its anchoring in business processes.
6.	The SKM approach needs to reflect KM activities (cf. KM at section 2.1), which are able to function as interventions and modify current environmental conditions [50].
7.	The SKM approach needs to reflect framework conditions of a KM (cf. KM at section 2.1). This requirement recognizes each activity to be realized within a certain environment and having influencing factors.

4 Design of a Symbiotic Knowledge Management Approach

Since not any contemporary KM considers educational perspectives and framework conditions, the following sets up a KM approach. Since the Potsdam KM Model has been identified as a powerful representative to carry out KM [15], it has served as starting point for an extension with BPO-KM framework conditions [31, 51, 52]. The approach designed is denominated as *KM approach* from hereon and its components have been indicated by highlighting the bottom left (blue) corner in Fig. 1.

Since not any contemporary KM further considers neuronal perspectives and not any approach to deal with ANN considers traditional KM activities, the following establishes a Neuronal Knowledge Management (short: NKM). Based on the requirements (cf. section 3), the *KM approach* mentioned before has been transferred to the neuronal context, so that a *NKM approach* has been constructed in a second step. Its components have been indicated by highlighting the top right (green) corner in Fig. 1.

In a third step, an approach has been designed, which issues the *ANN Process Domain*, and therefore integrates the KM approach from the *Process Domain* and the NKM approach from the *ANN Domain* [37]. In the following, this integrating approach is called Symbiotic Knowledge Management approach (short: *SKM approach*). With regard to Req. 1, it has been composed and therefore addresses activities from the one domain in the other domain and vice versa. The joint KM and NKM components of the SKM approach have been indicated by a gray shading in Fig. 1. Hence, by their joint visualization, the integration of three individual approach becomes transparent. Each of their components are issued in detail by the following sub-sections.

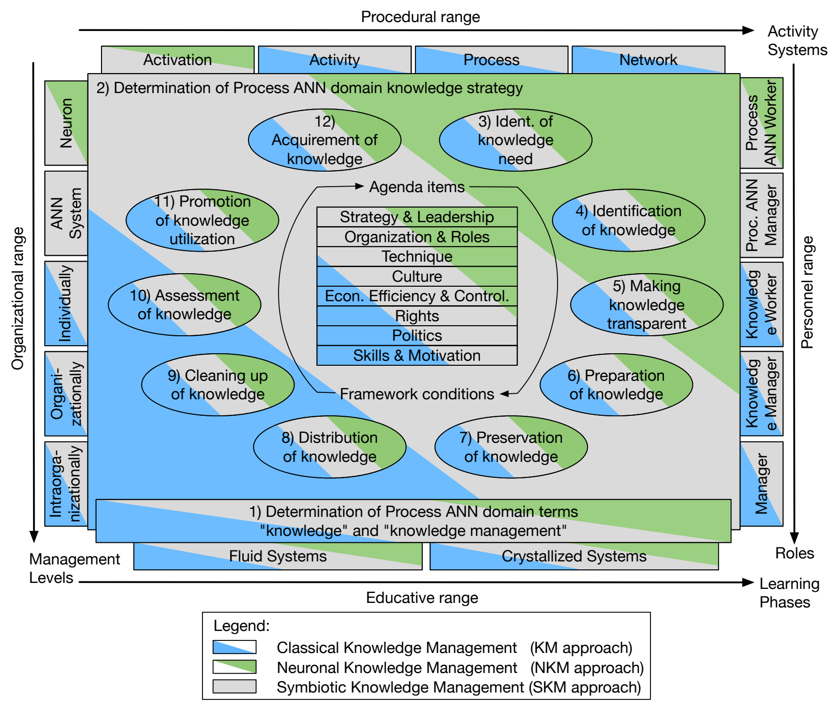

Fig. 1: The Design of the Symbiotic Knowledge Management Approach.

Activity Collection Beside the classical KM activities, that have been described by the Potsdam KM Model (cf. [15, p. 49]), the SKM approach and the NKM approach consider the same activities within the ANN domain. Although having the same naming, they follow an interpretation within the neuronal context. Jointly, they are referred to as *ordering amounts*. Hence, the Tab. 2 provides a new structuring of activities for the dealing with ANN systems by a reinterpretation of KM activities. The numbers visualized in Fig. 1 refer to the following explanations but they do not represent a sequential order.

Educative Range Specification The educative range of Fig. 1 focuses on the question, in which phase the learning system currently is, so that KM and NKM measures support the target-oriented knowledge development. This considers the type of the system, its individual capacities and learning burdens as well as its current knowledge state (cf. knowledge development at section 2.1). The educative range is supported by pedagogical valuable interventions. Its manifestations are ordered by the learning progress of management levels. Since an educative proceeding has not been considered by any KM approach, yet, and all activities of section 4 are affected by the educative range, Tab. 3 deals with differences between the KM approach, NKM approach and SKM approach.

Table 2: Activities for Managing Human and Artificial Knowledge Bearers.

ID	Description
1.	*Determination of terms:* A common understanding of relevant terms is established, so that the whole organization is able to communicate efficiently. In the case of the SKM approach, this refers to the terms of "knowledge" and "knowledge management", which reflect the *ANN Process Domain*. The KM approach would address the process-oriented KM context only (*Process Domain*) and the NKM approach would focus on terms about the dealing with ANN (*ANN Domain*).
2.	*Determination of knowledge strategy:* Being part of the organizational strategy, the importance of knowledge is determined from both, the KM and NKM perspective. While the KM approach disregards NKM objectives and the NKM approach disregards KM objectives, the SKM approach regards all kinds of objectives.
3.	*Identification of knowledge need:* Beside the identification of KM-based knowledge needs issued by the KM approach, the NKM approach examines on an individual level of a group of neurons, which kind of knowledge is required for an effective process step realization and knowledge generation. The SKM approach identifies the need on all kinds of management levels.
4.	*Identification of knowledge:* Beside the recognition of the personal, organizational and inter-organizational knowledge base issued by the KM approach, the joint knowledge base of ANN systems is examined by the SKM approach in regard to the currently available knowledge. This includes ANN-based knowledge representations of the NKM approach.
5.	*Making knowledge transparent:* Beside the identification and visualization of knowledge of internal and external knowledge carriers (knowledge workers) by the KM approach, the NKM approach identifies knowledge on a neuronal level. Going beyond, the SKM approach identifies knowledge of any kind of neuronal level, makes it transparent by visualizations and supports its access by meta information for ANN systems and human knowledge carriers.
6.	*Preparation of knowledge:* In harmony with the KM approach, the SKM approach issues the idea that knowledge is transformed to a KM-friendly and a NKM-friendly form. This allows the efficient use in current and future task realizations. In distinction of the SKM approach, the NKM approach transforms knowledge to a NKM-friendly form only, which disregards the KM-friendly form.
7.	*Preservation of knowledge:* Beside the structuring, decontextualization and backing up knowledge from the KM perspective, the SKM approach and the NKM approach consider the structuring and backing up of ANN-based knowledge. Just the SKM approach harmonizes the structuring and backing up of knowledge, so that an effective exchange of ANN-based and human knowledge is supported.
8.	*Distribution of knowledge:* A knowledge distribution within the organization must not be limited with respect to by management or by culture induced knowledge distributions, as the KM approach issues. The NKM approach issues the distribution of knowledge within ANN systems. The SKM approach further supports the distribution of ANN systems and knowledge generated by them within the organization. It further supports the distribution of knowledge of the organization within ANN systems.
9.	*Cleaning up of knowledge:* Beyond the correction, renewing and deletion of knowledge by the KM approach, the NKM approach cares about the correction, renewing and deletion of ANN-based knowledge. So, negative effects of knowledge not supporting the organization's objectives can be avoided.
10.	*Assessment of knowledge:* The assessment of the current knowledge base of an organization in regard to its value within the entire value chain is issued by the KM approach. The SKM approach additionally includes the assessment of the knowledge base generated by ANN systems. The NKM approach limits the knowledge assessment on neuronal systems only.
11.	*Promotion of knowledge utilization:* In addition to the creation and modification of new organizational structures, processes and systems that support the knowledge use (KM approach), the SKM approach includes the creation and modification of new ANN structures, systems, subsystems and neurons. The NKM approach only focuses on the transmission of neuronal signals and is with regard to the ANN performance.
12.	*Acquirement of knowledge:* In distinction from the elimination of a knowledge deficit by external acquisition or education, which is issued by the KM approach, the ANN knowledge deficit is treated by the NKM approach. Since the SKM approach includes the KM and NKM, the knowledge acquisition by education or external parties is considered for ANN system deficits, as well as ANN systems are considered for the elimination of a knowledge deficit within an organization.

Although various phases are adequate for an educative development of learning systems, as a rough first level, pedagogical and cognitive-psychological types of systems and corresponding learning phases, capacities and burdens have been considered. Further possibilities refer to e.g. the refinement of phases for different kinds of systems, such as phonological loop, episodic buffer, visuo-spatial sketch pad, central executive, or the six competence levels of Bloom, such as *Knowing*, *Comprehending*, *Applying*, *Synthesizing*, *Analyzing* and *Evaluating* [53]. The essential point of this range rather refers to the systematic education of learning systems than the concrete design. A comparable training and testing procedure for ANN systems has not been issued in literature, yet.

Table 3: Learning Phase-Specific Systems of Human and Artificial Knowledge Bearers.

ID	Description
1.	*Fluid Systems:* During the first learning phase, capacities are addressed by measures and activities, that reduce learning barriers and enable the schemata building in fluid systems. While KM measures and activities address capacities of traditional knowledge workers and human process participants, NKM measures and activities address capacities of ANN systems and machine-based process participants. The SKM approach considers KM measures and NKM measures jointly, so that interdependencies can be treated.
2.	*Crystallized Systems:* During the second learning phase, free capacities for the storing of fluid schemata are addressed, so that knowledge crystallizes and is integrated with and anchored in the crystallized knowledge base sustainably. Primary, KM measures and activities address the crystallization of schemata of traditional knowledge workers and human process participants, that have been built during the first learning phase. Corresponding NKM measures and activities address the crystallization of schemata of ANN systems and machine-based process participants. The SKM approach jointly considers the sustainable knowledge anchoring of schemata coming from any kind of fluid system.

Organizational Range Specification The organizational range of Fig. 1 focuses on the question, which areas of an organizational structure are affected by a KM measure and its concrete KM activities [15, p. 49]. Its manifestations are ordered by the amount and size of organizational structures participating in a certain KM measure. While the NKM approach only considers the level of *Neurons* to be affected by NKM measures and NKM activities, for the SKM approach, the KM approach has been extended by the elements of *ANN Systems* and *Neurons*, so that a NKM is enabled. Tab. 4 presents an overview.

Table 4: Management Levels for Managing Human and Artificial Knowledge Bearers.

ID	Description
1.	*Neuronal:* The neuronal manifestation issues the very atomic knowledge carriers as management level. It refers to compartments that jointly construct individual ANN systems.
2.	*ANN System:* The ANN system manifestation substantiates higher management levels, such as the *individual* in whatever detail by ANN mechanisms and algorithmic representations, the manifestation of ANN systems issues KM and NKM measures or rather activities that affect neuronal representations.
3.	*Individual:* Beside the idea, that KM measures and activities affect persons like Max Mustermann, issued by the KM model, the SKM approach includes the idea that these affect ANN systems as well. Since NKM measures and activities also affect individuals, the SKM approach integrates the *Process Domain* and the *ANN Domain*.
4.	*Organizational:* The SKM approach introduces the idea that NKM measures and activities can affect organizational entities, such as groups, teams, departments and sections. These in turn affect ANN systems by KM measures.
5.	*Intraorganizational:* Going beyond the traditional addressing of the collaboration between enterprises as well as the relation to suppliers and external service providers e.g., the SKM approach reflects NKM measures and activities for the affecting of intraorganizational entities.

Since dealing with knowledge is recognized throughout all management levels presented and the interplay of these levels is enabled because of a joint knowledge definition (cf. knowledge at section 2.1), the social construction of knowledge is reflected in the management approaches designed.

Procedural Range Specification The procedural range of Fig. 1 focuses on the question, which areas of a process organization are affected by a KM measure and its concrete KM activities [15, p. 49]. Its manifestations are ordered by a kind of complexity and complicatedness of manifestations participating in a certain KM measure. The KM approach has been extended by the element of addressing neuronal activities, the so called

Activation. So, a NKM is enabled by neuronal activities, which are relevant for a certain behavior of an ANN system. Tab. 5 presents an overview.

Table 5: Activity Systems Considering Human and Artificial Knowledge.

ID	Description
1.	*Activation:* As the key activity on the neuronal level (cf. artificial knowledge bearers at section 2.1), the neuronal activity brings together ANN mechanisms from the *ANN Domain* and a process understanding of the process domain. It refers to the most atomic activity system available at all and translates measures of a KM as well as a NKM to the neuronal context.
2.	*Activity:* The activity manifestation of the KM approach addresses the idea, that a measure or activity of KM can affect an individual activity. By the SKM approach, additionally, NKM-based measures and activities are also assumed to affect individual activities. So, the SKM approach addresses an integrative activity understanding in the sense of the *ANN Process Domain*: first, measures or activities of KM can affect corresponding ANN representations, second, measures or activities of NKM can affect activities of process participants and knowledge carriers. The NKM approach is designed to not consider this kind of activity system, since NKM measures and activities focus on the efficient Machine Learning task realization.
3.	*Process:* Since measures or activities of NKM are also considered to affect entire processes, and measures or activities of KM can affect corresponding ANN representations, the SKM approach addresses an integrative process understanding in the sense of the *ANN Process Domain*. The NKM approach is designed to disregard this kind of activity system, since NKM measures and activities focus on the efficient Machine Learning task realization.
4.	*Network:* The network manifestation of the KM approach issues the most complex and complicated activity system level of non-sequential processes, that must be considered as a mesh of processes. In addition, the SKM approach considers also measures or activities of NKM to affect entire networks, and measures or activities of KM to affect corresponding ANN representations. Having a clear focus of NKM measures and activities, the NKM approach disregards this kind of activity system.

Personnel Range Specification The personnel range of Fig. 1 focuses on the question, which persons are part of the realization of a KM measure and carry out concrete KM activities [15, p. 49]. Its manifestations are ordered by a kind of professional hierarchy. The KM approach has been extended by the element of *Process ANN Manager* and *Scientific Expert*, so that a NKM is enabled. So, Tab. 6 issues implications from the KM approach, NKM approach and SKM approach.

Framework Conditions The framework conditions of Fig. 1 focus on the question, which environmental agenda items need to be addressed by a KM measure and its concrete KM activities. Its manifestations jointly refer to [52, p. 109, 108, 107, 113] and [15] and do not have an ordering. As these are considered in the neuronal context, Tab. 7 issues implications from the KM approach, NKM approach and SKM approach.

5 Demonstration of New Knowledge Management Approaches

As demanded by the design-oriented research [2], the demonstration applies designed artifacts and demonstrates their use. Being faced with numerous management activities at the SKM approach and NKM approach the following exemplifies the use of each new approach by one scenario. Since the KM approach corresponds to an extension of traditional KM attempts and the KM approach is part of the SKM approach, it will be be demonstrated with the latter approach jointly.

Table 6: Roles for Managing Human and Artificial Knowledge Bearers.

ID	Description
1.	*Manager:* Beside the persons caring about the efficient realization of a model, which is issued by the KM approach, because of the SKM approach, the manager will be faced with the efficient and economic realization of a model of the *ANN Process Domain*. Focusing on the NKM approach only, this does not consider the management role directly, because the effect of a manager is decoupled from the technical Machine Learning task realization.
2.	*Knowledge Manager:* The knowledge manager cares about the efficient dealing with the resource of knowledge within the company [54]. As the SKM approach establishes a NKM in addition, the knowledge manager includes knowledge generated by ANN systems, subsystems and neurons, so that the organizational knowledge base is supplemented. Since knowledge managers are not considered for the technical Machine Learning task realization, these rather serve as domain-specific experts for the design, the NKM approach does not consider this kind of role directly.
3.	*Knowledge Worker:* According to the KM approach, the process participant is referred to as knowledge worker, that carries out knowledge-intensive processes. In the context of the SKM approach, the knowledge worker will also operate with the ANN constructed. It further enables the ANN construction by its process experience. Additionally, autonomous systems are considered as knowledge worker on an equal footing with human workers.
4.	*Process ANN Manager:* This role must be seen as counterpart of the knowledge manager. The process ANN manager cares about the efficient dealing with the resource of knowledge within a company on behalf of contemporary *ANN Process Domain* approaches. Since neither the NKM approach nor the KM approach consider systems from the other domain, this role functions as a bridge between different kinds of systems.
5.	*Process ANN Worker:* As a kind of complement for the process ANN manager, the process ANN worker issues the very specific competence of an scientific expert. It provides expertise from at least one domain that enables the *ANN Process Domain*. Here, one can find the wide range of biologists, neuro-scientists, and doctors, who care about state-of-the-art biologic mechanisms, as well as computer scientists and simulation experts caring about the algorithmic processing of simulations. Further, one can find ANN experts caring about the ANN system building, as well as experts from the specific field of application (e.g. chemist, physicians, astronomers, engineers). While the NKM approach considers this role only for the application of NKM measures, a classical KM approach so far has not accessed this kind of role because of the focus on KM measures and activities.

5.1 Interventions by the NKM Approach

Focusing on the artificial knowledge base of an ANN system design only, the use of the NKM approach can be demonstrated as follows: Imagine in this scenario to realize interventions addressing the different activities and learning phases. These are realized by the *Process ANN worker*, who is operating on an *Activation* level by the dealing with *Neurons*. Please trace this by the green components presented at Fig. 1 (highlighted top right corner).

For the initialization of an ANN system, the architectural structures are set up and weights are initialized randomly [55]. This refers to the NKM activity *Acquirement of knowledge* on the *Fluid System* level. The specification of training material can be associated with the activity called *Preparation of knowledge*. Of course, this material needs to be prepared by data experts before (fourth NKM activity, cf. Fig. 1). Here, an intervention could improve the expert's skills for this kind of knowledge identification.

As one e.g. recognizes compartments of an ANN to generalize efficiently, the knowledge utilization can be promoted by the reuse of these structures for the design of further ANN systems (eleventh NKM activity). For instance, it has been identified that a certain target system needs to establish a behavior, which is comparable to the behavior of the reference system (third NKM activity - *Identification of knowledge need*). Then, attractive structures of the reference system can be recreated at the target system (eighth NKM activity). In the case one aims to transfer ANN compartments from one customer to another, the framework conditions of *Rights* must allow this.

In the case, a system generates unpleasant recommendations, which have been identified because the corresponding knowledge has been assessed (tenth NKM activity),

Table 7: Framework Conditions for Managing Human and Artificial Knowledge Bearers.

ID	Description
1.	*Strategy & Leadership:* The KM approach focuses on traditional measures for an active management, that supports an autonomous, self-determined acting of process participants. In particular, this refers to the acting as coach and to the acknowledging of employees and external knowledge carriers [52, p. 109]. On the other side, the NKM approach issues measures for an active management supporting the self-determined acting of ANN systems as well as the acting as coach for ANN-based knowledge carriers. Considering all of them, the SKM approach provides measures for an active management by and of ANN systems as well as human process participants, which includes the educative knowledge development.
2.	*Organization & Roles:* In addition to measures providing appropriate processes, roles and an internal organization of communities to embed KM services in a company's structure, the NKM approach addresses measures for the provision of appropriate processes, roles and communities for the embedding of NKM services. Jointly, the SKM approach addresses corresponding measures for the embedding of KM services and NKM services.
3.	*Technique:* The KM approach focuses on measures for the establishment of an appropriate infrastructure, software and hardware, that allows the provision and utilization of KM services. As a supplement, the SKM approach cares about the provision of an appropriate infrastructure, software and hardware, which allows the provision and utilization of NKM services as well.
4.	*Culture:* Measures need to address attitudes, qualifications, role understanding and missions of actors of the social system, which all support the utilization of KM services and reduce barriers. In the sense of the SKM approach, all of them also need to support the utilization of NKM services. In this way, knowledge will be recognized as procedural phenomenon being able to be managed by an adequate environment.
5.	*Economic Efficiency & Controlling:* The KM approach demands for measures about the assurance of the beneficial, cost- and time-effective KM service use for the social system actors. It further addresses the examination of the successful realization of predefined KM targets. The SKM approach additionally includes the audit of the beneficial, cost- and time-effective NKM service utilization and the fulfillment of predefined NKM targets by hard and soft indicators. It so builds on the NKM approach.
6.	*Rights:* The KM approach demands for measures about the assurance of legal issues, such as property rights of third parties and conditions for governmental approvals about the provision of KM services, as well as for the explanation of rights and duties for knowledge workers, that are relevant for the dealing with KM services. In distinction from this approach, the NKM approach issues the compliance of legal issues of NKM services and the explanation of rights and duties for the dealing with NKM services. Going beyond, the SKM approach draws attention to all.
7.	*Politics:* In addition to KM approach measures providing organizational resources in regard with legal circumstances, that allow the use of KM services, the NKM approach builds on governmental regulations affecting the provision of organizational resources, that allow the use of NKM services, and tries to adjust legal circumstances. The SKM approach jointly draws attention to all.
8.	*Skills & Motivation:* Going beyond measures of the KM approach, that demand for an enhancement of individual skills that are relevant for business process realizations, and the motivation of employees to conduct effective KM activities [52, p. 108], the SKM approach demands for the enhancement of individual skills relevant for neuronal process realizations, and the motivation of employees to conduct effective NKM activities. It so builds on the NKM approach.

these ANN compartments simply can be deleted, which are responsible for this recommendation (ninth NKM activity - *Cleaning up of knowledge*). This might be related to political regulations (framework condition of *Politics*), as for example laws demand for the transparent backing up of data and information systems.

When learning has finalized successfully, and one intends to continue training processes, it might be useful to preserve the current ANN structures as crystallized memories (second learning phase). By the provision of new capacities, such as additional neurons at the ANN trained, these can focus on fluid knowledge while crystallized structures care about learned memories (seventh NKM activity - *Preservation of knowledge*).

5.2 Interventions by the SKM Approach

Focusing on the organization-wide knowledge base, the use of the SKM approach can be demonstrated as follows. Imagine in this scenario to realize interventions addressing the different activities and learning phases. These are addressed by all kinds of roles, that are operating on all kind of activity systems (procedural range). Further, they are dealing with all kinds of management levels (organizational range). Please trace this by the gray components presented at Fig. 1 (shaded components).

Let's assume to initialize ANN systems again (*Fluid System* level). The *Knowledge Worker* can guide the knowledge identification best because of its experiences from the daily routines in the knowledge-intensive process that is issued (fourth SKM activity). For this, the *Knowledge Manager* guides the selection of knowledge workers across the processes. Here, the knowledge manager reflects the *Activity* level since knowledge is identified at the realization of an operational task. Further, the knowledge manager reflects the *Process* level because knowledge from the one task will be distributed among other tasks. The *Manager* cares about the consideration of economic dimensions and the organization's vision. E.g. the manager intends do "reduce process durations" by the reuse of knowledge across the processes (eighth SKM activity). Here, he focuses on the *Network* level. The *Process ANN Worker* finally trains the ANN systems. The *Process ANN Manager* regards the training progress and cares e.g. about the efficient implementation of the knowledge acquisition. This includes the backing up of knowledge and ANN systems by the marking as *crystallized system*.

An example for the interplay of all kinds of management levels refers to the following: Let's assume to have established a crystallized organizational knowledge base, which e.g. can be seen at the availability of standards, routines and a team-wide behavioral pattern (*Organizational* management level). Then, a new colleague (*Individual* level) or intelligent machine (*ANN System* level) might cause a change of this long-term memory because of the integration of new knowledge objects and the current knowledge base. Here, it is essential that the organization's culture (fourth framework condition) supports the inclusion of external expertise.

6 Evaluation

In order to satisfy design-science-oriented research approaches [2], the following evaluates how far requirements of section 3 have been fulfilled.

- Req. 1 has been fulfilled, as three kinds of KM approaches have been superpositioned. By this, the three kinds of approaches (KM / NKM / SKM) can stand individually within its own domain, or they can integrate the *Process Domain*, the *ANN Domain* and the *ANN Process Domain*.
- Req. 2 has been fulfilled, as contemporary knowledge bearers (or management levels) have been considered by the SKM approach on an equal footing. Here, the traditional ontological levels, such as *Individuals*, *Organizations* (groups, teams, departments) and *Intraorganizations*, have been positioned next to AI-based systems, such as *ANN Systems* and its compartments (*Neurons*).
- Req. 3 has been fulfilled, as contemporary pedagogical concepts have been considered by the SKM approach. Here, learning phases have been put side-by-side, so that a focus is set on the dealing with fluid and crystallized systems.
- Req. 4 has been fulfilled, as contemporary roles have been considered by the SKM approach on an equal footing. Here, traditional ontological levels, such as the *Manager*,

the *Knowledge Manager* and *Knowledge Worker* have been positioned next to the novel roles of *Process ANN Managers* and *Process ANN Workers*.
- Req. 5 has been fulfilled, as contemporary activity systems have been considered by the SKM approach. Here, traditional systems, such as *Activities*, *Processes* and *Networks*, have been positioned next to AI-based systems (*Activations*).
- Req. 6 has been fulfilled, as different kinds of KM activities have been considered by the SKM approach. With this, a systematic ANN system realization is enabled by the NKM.
- Req. 7 has been fulfilled, as environmental factors have been considered by the SKM approach by categories or rather agenda items.

7 Conclusion

Having updated traditional KM by one further approach (KM approach), and having formulated a neuronal knowledge management and its approach (NKM approach), further, a joint approach has been created (SKM approach). This considers human as well as artificial knowledge bearers to be in a symbiosis, and with whom they jointly can be managed. The approach components have been demonstrated individually, so that the approach interplay and the accessing of its individual domains has been clarified.

Critical appraisal: The first research question (*"How can AI-based systems be considered as knowledge bearers, so that traditional KM is enhanced?"*) can be answered with the design of the SKM approach. The traditional KM can be enhanced as ANN systems are considered as a new kind of knowledge bearers, which are treated on an equal footing with traditional knowledge bearers. By this, a more powerful organization-wide knowledge base can be accessed, that includes decentralized individual knowledge bases of autonomous machines.

The second research question (*"How can human knowledge be considered at knowledge-driven enterprise information systems, so that dealing with AI-based systems is enhanced?"*) can be answered by the design of the NKM approach, which transfers traditional KM activities and framework conditions to the context of ANN system designs. For the first time, the dealing with ANN-based knowledge can be systematized, which results in new activities in the training and testing of ANN systems. Oriented to contemporary psychological concepts, this further considers different learning phases and introduces a pedagogical valuable, incremental knowledge building in the dealing with ANN systems.

So, the main research question (*"How can machine-based knowledge and human-based knowledge be managed efficiently in an integrated way?"*) can be answered by the joint consideration of machine-based and human knowledge by one management approach. This is based on the superposition of a traditional KM and the new form of neuronal KM, so that the joint SKM is set up in the *ANN Process Domain*. This claims to be efficient, as ANN-based knowledge becomes manageable for the first time and further considers interdependencies among the different kinds of KM approaches. Further, because of the pedagogical valuable addressing of capacities, learning burdens and emotional factors, the efficient and learner-specific management is supported. As a wide research field of the operationalization of this new kind of management, the concrete addressing of them by valuable pedagogic designs and Machine Learning algorithms need to be examined.

Limitations: Although first use cases demonstrate the use of NKM approach and SKM approach, only a sparse collection of theoretical use cases has been presented. However, these focused on the exemplary clarification of measures or interventions of the one domain affecting the other and the complete demonstration of the ordering system has not been presented, yet. Further, the validity level is low as demonstrations presented refer to abstract descriptions only.

Outlook: Faced with given limitations, the collection of use cases is to be extended. This must include the circumstantial description of technical effects by an activity. With this, the initial assumption of having a potential for organizations, because of the joint management of human kinds as well as technical kinds of knowledge bearers, needs to be verified empirically. Further, it will be examined, how far the trustworthy and ethical justifiable use of AI-based systems is supported with the aid of the SKM approach and NKM approach.

References

1. A. Begler and T. Gavrilova, "Artificial intelligence methods for knowledge management systems," Working Papers 15106, Graduate School of Management, St. Petersburg State University, 2018.
2. K. Peffers, T. Tuunanen, C. E. Gengler, M. Rossi, W. Hui, V. Virtanen, and J. Bragge, "The design science research process: A model for producing and presenting information systems reseach," *1st International Conference on Design Science in Information Systems and Technology (DESRIST)*, vol. 24, pp. 83–106, 8 2006.
3. J. Eberhard, *Johann August Eberhards synonymisches Handwörterbuch der deutschen Sprache*. Schimmelpfennig, 1802.
4. P. Schlabach, *Sitte, Ethik und Moral: eine Begründung*. tredition, 2018.
5. L. Wittgenstein, *Philosophische Untersuchungen*. Frankfurt am Main: Suhrkamp Verlag, 1953.
6. P. Prechtl and F. Burkard, *Metzler Lexikon Philosophie: Begriffe und Definitionen*. J.B. Metzler, 2015.
7. E. Brendel, "Wissen," in *Lexikon Philosophy - Hundert Grundbegriffe* (S. Jordan and C. Nimtz, eds.), pp. 308–311, Reclam, 2013.
8. E. L. Gettier, "Is justified true belief knowledge?," *Analysis*, vol. 23, no. 6, pp. 121–123, 1963.
9. F. E. Weinert, "Vergleichende Leistungsmessung in Schulen - eine umstrittene Selbstverständlichkeit," in *Leistungsmessungen in Schulen* (F. E. Weinert, ed.), pp. 17–32, Weinheim: Beltz, 2001.
10. V. Heyse and J. Erpenbeck, *Kompetenztraining: 64 modulare Informations- und Trainingsprogramme für die betriebliche, pädagogische und psychologische Praxis*. Schäffer-Poeschel, 2009.
11. C. Schmidt, "Arbeitsgedächtnis und fremdsprachliches leseverstehen," *Zeitschrift für Fremdsprachenforschung*, vol. 1, no. 11, pp. 83–101, 2000.
12. M. Wellenreuther, *Forschungsbasierte Schulpdagogik*. Schneider Verlag Hohengehren, 2012.
13. T. H. Davenport and L. Prusak, "Working knowledge: How organizations manage what they know," *Ubiquity*, vol. 2000, Aug. 2000.
14. M. Polanyi and A. Sen, *The tacit dimension*. University of Chicago Press, reissue ed., May 2009.

15. N. Gronau, *Wissen prozessorientiert managen: Methode und Werkzeuge für die Nutzung des Wettbewerbsfaktors Wissen in Unternehmen*. Oldenbourg Wissenschaftsverlag, 2009.
16. K. North, A. Brandner, and T. Steininger, *Die Wissenstreppe: Information – Wissen – Kompetenz*, pp. 5–8. Wiesbaden: Springer Fachmedien Wiesbaden, 2016.
17. U. Lämmel and J. Cleve, *Künstliche Intelligenz*. München: Carl-Hanser Verlag, 2012.
18. R. L. Solso, *Kognitive Psychologie*. Springer-Lehrbuch, Heidelberg: Springer, 2005.
19. G. Reinmann-Rothmeier and H. Mandl, "Wissen," in *Lexikon der Neurowissenschaft*, Spektrum Akademischer Verlag, Heidelberg, 2000.
20. J. Girard and J. Girard, "Defining knowledge management: Toward an applied compendium," *Online Journal of Applied Knowledge Management*, vol. 3, no. 1, pp. 1–20, 2015.
21. A. Scheer, *ARIS - Modellierungsmethoden, Metamodelle, Anwendungen*. 3, Springer Berlin Heidelberg, 1998.
22. J. Becker, R. Schütte, T. Geib, and H. Ibershoff, "Grundsätze ordnungsmäßiger modellierung (gom)/westfälische wilhelms-universität münster–institut für wirtschaftsinformatik, ids scheer ag, josef friedr," *Bremke & Hoerster GmbH & Co*, 2000.
23. U. Remus, "Prozessorientiertes wissensmanagement. konzepte und modellierung," Juni 2002.
24. P. Fettke and P. Loos, "Referenzmodellierungsforschung," *WIRTSCHAFTSINFORMATIK*, vol. 46, pp. 331–340, Oct 2004.
25. N. Gronau and C. Müller, "Wissensarbeit prozessorientiert modellieren und verbessern," 2005.
26. N. Gronau, C. Müller, and R. Korf, "Kmdl - capturing, analysing and improving knowledge-intensive business processes," *Journal of Universal Computer Science*, vol. 11, pp. 452–472, apr 2005.
27. K. Hinkelmann, B. Thönssen, and F. Probst, "Referenzmodellierung für e-government-services," *Wirtschaftsinformatik*, vol. 47, no. 5, pp. 356–366, 2005.
28. T. Davenport, S. Jarvenpaa, and W. Beers, "Improving knowledge work processes," *Sloan Management Review 37*, no. 4, pp. 53–65, 1996.
29. T. Allweyer, "Modellbasiertes wissensmanagement," *Information Management*, vol. 13, no. 1, pp. 37–45, 1998.
30. K. Hinkelmann, D. Karagiannis, and R. Telesko, *PROMOTE — Methodologie und Werkzeug für geschäftsprozessorientiertes Wissensmanagement*, pp. 65–90. Berlin, Heidelberg: Springer Berlin Heidelberg, 2002.
31. P. Heisig, *Geschäftsprozessorientiertes Wissensmanagement: effektive Wissensnutzung bei der Planung und Umsetzung von Geschäftsprozessen*, ch. GPO-WM: Methode und Werkzeug zum geschäftsprozessorientierten Wissensmanagement, pp. 47–64. Xpert.press, Berlin Heidelberg: Springer Berlin Heidelberg, 2002.
32. S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*. USA: Prentice Hall Press, 3rd ed., 2009.
33. N. Bostrom, *Superintelligence: Paths, Dangers, Strategies*. USA: Oxford University Press, Inc., 1st ed., 2014.
34. P. Fettke, "Conceptual modelling and artificial intelligence: Overview and research challenges from the perspective of predictive business process management," in *Companion Proceedings of Modellierung 2020 Short, Workshop and Tools & Demo Papers co-located with Modellierung 2020, Vienna, Austria, February 19-21, 2020*, pp. 157–164, 2020.
35. M. Peschl, *Cognitive Modelling: Ein Beitrag zur Cognitive Science aus der Perspektive des Konstruktivismus und des Konnektionismus*. DUV: Datenverarbeitung, Deutscher Universitätsverlag, 1990.
36. J. Evermann, J.-R. Rehse, and P. Fettke, "Predicting process behaviour using deep learning," *Decision Support Systems*, vol. 100, pp. 129 – 140, 2017. Smart Business Process Management.

37. M. Grum and N. Gronau, "A visionary way to novel process optimization techniques - the marriage of the process domain and deep neuronal networks," in *Springer LNBIP*, pp. 1–24, 2018.
38. A. Baddeley, "Oxford psychology series, no. 11. working memory. new york, ny, us," 1986.
39. A. J. Baddeley, "The episodic buffer: a new component of working memory?," *Trends in Cognitive Sciences*, vol. 4, pp. 417–423, 2000.
40. A. Baddeley, "Working memory: Theories, models, and controversies," *Annual Review of Psychology*, vol. 63, no. 1, pp. 1–29, 2012. PMID: 21961947.
41. J. Sweller, J. J. G. van Merrienboer, and F. G. W. C. Paas, "Cognitive architecture and instructional design," *Educational Psychology Review*, vol. 10, pp. 251–296, Sep 1998.
42. R. C. Clark, F. Nguyen, J. Sweller, and M. Baddeley, "Efficiency in learning: Evidence-based guidelines to manage cognitive load," *Performance Improvement*, vol. 45, no. 9, pp. 46–47, 2006.
43. D. Lufi, S. Okasha, and A. Cohen, "Test anxiety and its effect on the personality of students with learning disabilities," *Learning Disability Quarterly*, vol. 27, no. 3, pp. 176–184, 2004.
44. H. Heymann, "Üben und wiederholen - neu betrachtet," *Pädagogik*, vol. 10, pp. 7–11, 1998.
45. M. Alavi and D. E. Leidner, "Review: Knowledge management and knowledge management systems: Conceptual foundations and research issues," *MIS Quarterly*, vol. 25, no. 1, pp. 107–136, 2001.
46. R. Weinreich and I. Groher, "Software architecture knowledge management approaches and their support for knowledge management activities: A systematic literature review," *Information and Software Technology*, vol. 80, pp. 265 – 286, 2016.
47. E. Tsui, B. J. Garner, and S. Staab, "The role of artificial intelligence in knowledge management," *Knowledge based systems*, vol. 13, no. 5, pp. 235–239, 2000.
48. S.-h. Liao, "Knowledge management technologies and applications—literature review from 1995 to 2002," *Expert systems with applications*, vol. 25, no. 2, pp. 155–164, 2003.
49. J. Schmidhuber, "Deep learning in neural networks: An overview," *Neural Networks*, vol. 61, pp. 85 – 117, 2015.
50. M. Grum, S. Rapp, N. Gronau, and A. Albers, "Accelerating knowledge - the speed optimization of knowledge transfers," in *Proceedings of the Nineth BMSD*, 2019.
51. P. Heisig, *Integration von Wissensmanagement in Geschäftsprozessen*. dissertation, Technische Universität Berlin, 2005.
52. K. Mertens, *Knowledge Management: Best Practices in Europe*. Berlin, Heidelberg: Springer-Verlag, http://publica.fraunhofer.de/documents/n-4420.html ed., 2001.
53. B. S. Bloom, M. B. Engelhart, E. J. Furst, W. H. Hill, and D. R. Krathwohl, *Taxonomy of educational objectives. The classification of educational goals. Handbook 1: Cognitive domain*. New York: Longmans Green, 1956.
54. G. Probst, S. Raub, and K. Romhardt, *Wissen managen - Wie Unternehmen ihre wertvollste Ressource optimal nutzen*. Gabler Verlag, 5 ed., 2006.
55. S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural computation*, vol. 9, pp. 1735–1780, 1997.