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REVIEW

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Self-organizing systems in the construction industry

Jessica Lohmann[1] | **Thomas Kölzer**[2] | **Gunnar Schaan**[1,3] | **Frank Schmidt-Döhl**[1]

[1]Institute of Materials, Physics and Chemistry of Buildings, Hamburg University of Technology, Hamburg, Germany

[2]Institute of Digital and Autonomous Construction, Hamburg University of Technology, Hamburg, Germany

[3]Electron Microscopy Unit, Hamburg University of Technology, Hamburg, Germany

Correspondence
Jessica Lohmann, Institute of Materials, Physics and Chemistry of Buildings, Hamburg University of Technology, 21073 Hamburg, Germany.
Email: jessica.lohmann@tuhh.de

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Abstract

Self-organization is found in numerous natural and artificial systems. For the construction industry, self-organizing processes are not only applicable in managing or organizing tasks, they also provide insight into materials or can be implemented into operations on building sites. In this paper, the terms *feedback*, *agents*, *emergence* and *self-organization* are described to provide an insight into the complex processes relevant to a lot of fields in the construction industry. For this, the principles of adaptive processes are transferred to artificial systems. Besides self-organization in building materials, an outlook is given to describe construction sites as cyber-physical systems. Inside such systems, agents learn to organize work tasks more efficiently, particularly with the help of reinforcement learning. In this regard, a transfer of natural self-organization—which also exist in materials—to building processes is made. A combination of natural and artificial systems is presented to promote self-organization for various fields of application in the construction industry, especially for building sites.

KEYWORDS

artificial intelligence, building materials, complex adaptive systems, construction industry, cyber physical systems, reinforcement learning, self-organization

1 | INTRODUCTION

Dynamic processes outside thermodynamic equilibrium occur in numerous natural phenomena. The formation of the universe and subsequent evolutionary processes that govern life on Earth can also be traced back to similar processes.[1] Over time, organisms have adapted their behavior to constantly changing environmental conditions. To describe dynamic processes, *Complex Adaptive System* (CAS) models can be used in many scientific disciplines. The models are applied, for example, to describe climate phenomena, biological cell activity, earthquake statistics, the human brain, or artificial intelligence.[2,3] Such systems are often characterized by a large number of components, normally referred to as agents, which interact with each other.[4] Agents are arranged through self-organization processes at different levels. They are also able to adapt and learn from each other. Every agent sends and receives signals (feedback), both to other agents and from the environment.[5] In doing so, they interact not only with agents of the same level, but also with agents of the entire system and with the environment. By making specific changes, they can improve the functionality of the system over time.[4]

Jessica Lohmann and Thomas Kölzer contribute equally as first authors.

CAS are further characterized by one or more levels of feedback, but also by the emergence of new properties,[6] and self-organization processes with nonlinear dynamic behavior.[2,4] The individual levels of a system are usually referred to as subsystems. The more subsystems, the more complex a system becomes. In many cases, hierarchical structures emerge that are capable of generating new emergent properties.[6] The aim of this work is to show connections between natural and artificial complex systems. As a basis, the general characteristics of CAS are described. The terms agents, feedback, self-organization and emergence are discussed in this article. Since the terms have specific meanings and are not used consistently in literature, it is important to define them first. Additionally, a general definition of the term self-organization is presented, which so far has not been used uniformly.

Self-organization processes are predominantly related to biological systems. This contribution shows, however, that the concept of CAS cannot only be applied to natural processes like evolution, but also to artificial systems. The focus of this paper is in the area of civil engineering. Two building materials—wood as a natural raw material and concrete as a fabricated material—are described as CAS. With this material-based introduction to the topic, new insights are presented regarding the application of self-organizing systems to an industrial sector not commonly associated with adaptive concepts. To show the extensive potential, an example of a construction site as a *cyber-physical system* (CPS) demonstrates the idea of combining basic knowledge of self-organization with technical processes in constantly changing environments.

2 | AGENTS IN SELF-ORGANIZING SYSTEMS

Each organism, particle or molecule operates as an individual object, or agent, in a complex system. Agents interact with the environment as well as with one another. They influence each other via feedback loops by sending and receiving signals and react to influences of the changing environment. Agents operate predominantly autonomously without external control. Rules and patterns are followed with local knowledge, where each agent is part of a large, global system. Using correlated feedback, agents produce emergent structures and patterns. They are largely similar and homogeneous within a subsystem, so if they misbehave, they can be easily replaced without affecting the functionality of the whole system.[6] In case agents are too heterogeneous, there is a risk of chaotic behavior and disruption of the emergent structure.[2]

Agents are capable to react and adapt to changing environmental influences. They are able to learn or even develop intelligent behavior.[4] Such an adaptation process can occur both at the agent level (*agent-level adaptation*) and at the system level (*system-level adaptation*). In agent-level adaption, the behavior of a single agent changes through learning or adaptation. In system-level adaptation, a correlated group of agents adapts to the environment. In doing so, they exhibit intelligent behavior with complex dynamics, even though each agent follows only simple patterns.[2] The adaptation of agents occurs over time and aims to improve the functionality of the system.[5] The view of complex systems with different levels is also relevant for construction sites, which will be discussed later.

3 | FEEDBACK

Self-organization processes are based on interactions between agents, resulting in complex patterns and emergent properties. The two fundamental types of interactions are positive and negative feedback. Positive feedback reinforces initial changes, leading to an acceleration of the changing of states. Negative feedback hinders or counteracts these changes, stabilizing the system. Self-organization processes begin with a positive feedback phase amplifying small fluctuations that initiate changes in the system.[7] In complex systems, however, multiple positive and negative feedback loops are present simultaneously. This steers the system in one direction or another without reaching a stable state of equilibrium. The consequence is nonlinear dynamical systems outside thermodynamic equilibrium.[8] In general, feedback can act from both inside and outside the system.[2]

4 | SELF-ORGANIZATION IN THERMODYNAMIC SYSTEMS

Self-organization can be defined as a process in which structures emerge without external control.[3,7] Self-organization takes place in a dissipative system in which energy input is required from an external source to maintain the integrity of the structure.[1]

Over time, an isolated system has the highest degree of disorder, and thus maximum entropy. Lowering entropy requires a flow of energy, which is not supplied to an isolated system. To achieve an increase in order, the process requires a thermodynamically open or closed system ensuring that energy can be transferred from the outside.[8] Entropy is decreased by energy dissipation that allows the formation of dissipative structures outside of thermodynamic equilibrium.[9] The system is embedded in and in constant exchange with a specific environment.[10]

Normally these changes are considered in basic research areas such as thermodynamics or biology. The transfer of this knowledge into new areas, however, has become more relevant since concepts related to artificial intelligence have attracted more attention in other fields, for example, the building industry. The construction of a new building always takes place in a new a surrounding. Furthermore, construction sites can also be seen as constantly changing environments. This will be discussed later in this paper.

In general, the environment offers some constraints for internal mechanisms.[10] However, the influences are not intended to provide direction, but merely initiate small changes in the system.[3,11] A change in external conditions can induce structural transformations. The observer must define the boundaries of the system. Gershenson and Heylighen define self-organization as “a way of modelling the system, not a class of systems.”[9] In this context, any dynamic system can be self-organized as long as it achieves the goals defined by an observer.[4] At the same time, these systems can also be disorganized on other levels and aspects.

Self-organizing processes are further characterized by their nonlinearity arising from feedback loops between individual agents in a specific system. The loops allow a system to move outside of thermodynamic equilibrium.[10] An energy input from the outside shifts the system out of thermodynamic equilibrium. The complex interactions between the components of the system result in an increase in the number of stable states, enabling the system to exhibit a more resilient response to perturbations and changes. Dynamic systems strive for thermodynamic equilibrium. In nonlinear systems, several attractive forces are present. If the system moves between these states, fluctuations occur that steer the system in one direction or another.[8]

Self-organization processes take place in dynamic systems. Interactions between individual agents at a local level generate a set of dynamic mechanisms at a global level. An increase in order within the system occurs. Thus, order emerges from the interacting agents as well as the conditions in local environments. An intentional separation of self-organization and contributing environmental influences is thereby made difficult and deemed impossible. Accordingly, self-organization is considered an interaction of internal and external sources of order. By increasing order in a system, temporal, functional or spatial structures can emerge.[3] The attributes of a system can be further divided into primary and secondary properties. Primary properties are characterized by the fact that the resulting features cannot be derived from others. An example of primary properties is the special characteristics resulting from interaction of positive and negative feedback in feedback loops. Accordingly, secondary properties are derived from primary properties.[10]

Another aspect to describe self-organization processes is the increase of complexity. Heylighen describes a self-organizing system as “thermodynamically open but organizationally closed,”[8] that is, it consists of several self-contained, autonomous subsystems that continue to interact with each other. Hierarchical structures emerge and complexity increases. The various subsystems create a coherent system from which new properties can arise. This classification of the properties is also relevant for data-based artificial systems; this will be discussed later when it comes to the distinction of information, for example, in digital twins for construction sites.

In self-organization processes, agents are able to respond and adapt to changes in the system. As a result, order of the system can be maintained independently of external interference. This phenomenon is supported by the fact that no distinction of individuals has to be made. Self-organization is also a time-dependent process. As time passes, order increases and the system becomes more sensitive to change, but at the same time is able to respond to it dynamically.

Many different definitions of self-organization exist. The term is often equated to emergence and it is likely that self-organization often appears in combination with emergence. The formation of structure via self-organization processes can be accompanied by the formation of functional properties. However, self-organization can also occur without emergence. The formation of structures and patterns in the system arises without the generation of functional properties. Based on the previous description of self-organization, we propose the following definition:

Self-organization describes the dissipative order of a system outside of thermodynamic equilibrium. The order is established by local interactions of individual components that create structures on a global scale. The system requires an external energy source, without which order cannot be maintained. Order arises from internal and external influences. External influences can initiate a structural transformation, but cannot set the direction. Self-organization is a time-dependent process that responds dynamically to change. It is an interplay of internal feedback loops at multiple levels. Nonlinearity allows for flexible adaptation and the generation of complex emergent properties. The boundaries of the system must be defined.

5 | EMERGENCE IN COMPLEX SYSTEMS

Emergence describes the formation of new properties as a result of interactions of agents within a system. The resulting properties are called emergent properties, for example, characteristics of the system, structures or patterns.[3] A distinction can be made between simple and complex emergent properties. Simple emergent properties arise in or near thermodynamic equilibrium. They are collective or global properties that can be inferred from the interactions of locally acting agents. The system properties are controllable and approximately linearly derivable from the properties of the agents.

On the other hand, complex emergent properties arise in nonlinear systems outside thermodynamic equilibrium and are controlled by an input of energy or matter. They often occur in conjunction with self-organization. Halley and Winkler define the transition from simple emergent properties to complex emergent properties as the onset of self-organization. As the system becomes more complex, self-organization processes emerge at multiple levels, and the system forms hierarchical structures.[1]

One important aspect to characterize complex emergence is the *micro–macro effect*. Agents interact collectively at a local level (microlevel) and generate global properties (macrolevel). In these processes, information at lower levels is transformed into information at higher levels. The properties of a system are no longer related to the properties of individual agents, for example, the stiffness of fibers and the elasticity of the matrix in fiber-reinforced polymers.[3,7]

The emergence of new global properties that cannot be derived from individual agents is described by the term *radical novelty*. This characteristic describes the behavior of a system as a whole. To model a system, individual agents must be considered in the context of the entire system. A prerequisite for emergence to occur in a system is persisting coherence and interaction between the agents in a dynamic system.[9] Properties and structures emerge over time. In this process, there is no control mechanism influencing global behavior. Only local influences, such as fluctuations in the system, can affect the microlevel agents and thus indirectly alter global properties. However, there is also a two-way relation. Changes in global properties can also affect the individual agents. As a result of these characteristics of emergence, the system is able to change in a flexible and robust manner. The fact that the properties of an individual agent do not directly affect the global behavior of the system means that individual agents can be replaced without disturbing the functionality of the system.[3]

6 | SELF-ORGANIZATION IN BUILDING MATERIALS

The principle of self-organization processes can be illustrated in a simple model (see Figure 1). An open system comprises several subsystems and is in exchange with the environment. Agents interact with other agents and the local environment. Additionally, the behavior of agents can also be indirectly influenced, for example, when one agent influences the environment, which in turn affects the performance of other agents.[7]

If the concepts are now transferred to practical examples from the construction industry, the representation becomes much more complicated. The more complex the system and the processes become, the more difficult it is to understand the relationships or to describe the interactions. For example, the production of building materials such as concrete or mortar can be regarded as a self-organizing system. During curing and hardening, individual particles of different energy levels, which can be considered as agents, interact. The inherent subsystems are definable by different particle sizes and surface properties.

As an initial trigger, energy is introduced into the system through the mixing process. The addition of water starts the hydration of the cement. Initially, a liquid cement paste is formed, which solidifies into hardened cement paste

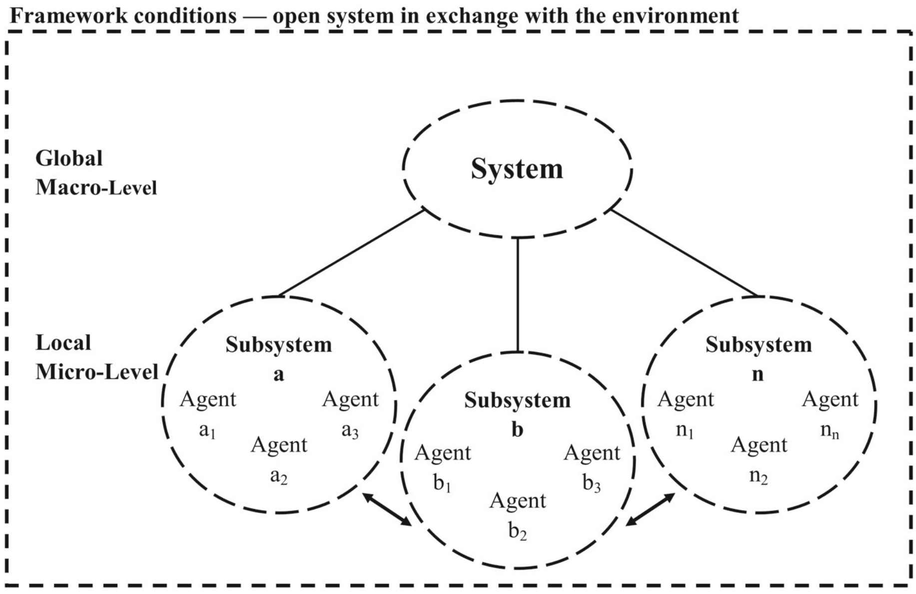

FIGURE 1 Simplified representation of complex adaptive systems.

through the onset of reactions. This, along with friction between individual particles, produces heat, which influences the processes in the system. The cement clinker phases form calcium silicate hydrate (C-S-H) and other phases which bond the aggregate together.[12] As hydration progresses and C-S-H phases are formed, the contact area between particles is reduced.

The rheological properties of the system are in constant flux. As a result, individual particles have fewer opportunities to arrange themselves; the entropy of the system is reduced.[13] Another constraint is the formwork as an active participant of the system. It, too, imposes certain constraints on the arrangement of particles in the concrete. At the same time, the formwork can be defined as a boundary.[11] The concrete in the formwork represents the system, and the individual particles constitute the subsystems at different levels. Particle sizes vary on the macro-, micro- or nanolevel. At the same time, all components interact with each other. If the observer shifts the boundaries of the system, the concrete can also be only a subsystem of a building component, which in turn is again a subsystem of a building.

Structural formation begins at the lowest level of a model. At the nanoscale, the formation of C-S-H phases begins as a result of thermofluctuations due to ionic motion. These generate new phase nuclei that lead to crystal growth and gel formation. Newly formed phases interact with both the dispersion medium and other particles in the solution, forming the microstructure. The dispersion medium and the particles also interact with one another, as do microstructure and macrostructure.

All components in the entire system interact with each other. Any change in one subsystem affects the organization of the other levels (see Figure 1). However, the changes can only initiate structural alterations, but not govern them.[11] The self-organization process starts internally through fluctuations and is influenced by external factors such as the formwork design. Due to changing rheological properties as well as surface energies, the system undergoes a dynamic structural transformation and generates a functional building material through ordering processes, which, for example, meets special requirements in the area of compressive strength or fire protection. The structure formation can also be influenced by a suitable selection of starting materials in order to achieve a high-packing density.

Timber is another example of building materials generated by self-organization. Wood is a biocomposite made of the polymers cellulose, hemicellulose and lignin. The formation and arrangement of the cells evolved over time to provide the plant with the best possible supply of water and nutrients as well as to resist mechanical influences. The organism tree can be considered a system that is in exchange with the environment. The individual cells, in turn, constitute subsystems in which various polymers interact with each other as agents. The cell wall has a complex structure consisting of several layers (see Figure 2). The outer layer is formed by the middle lamella (M), followed by the primary wall (P). Interior to the primary wall is the secondary wall (S), which is further divided into S1, S2 and S3.[14]

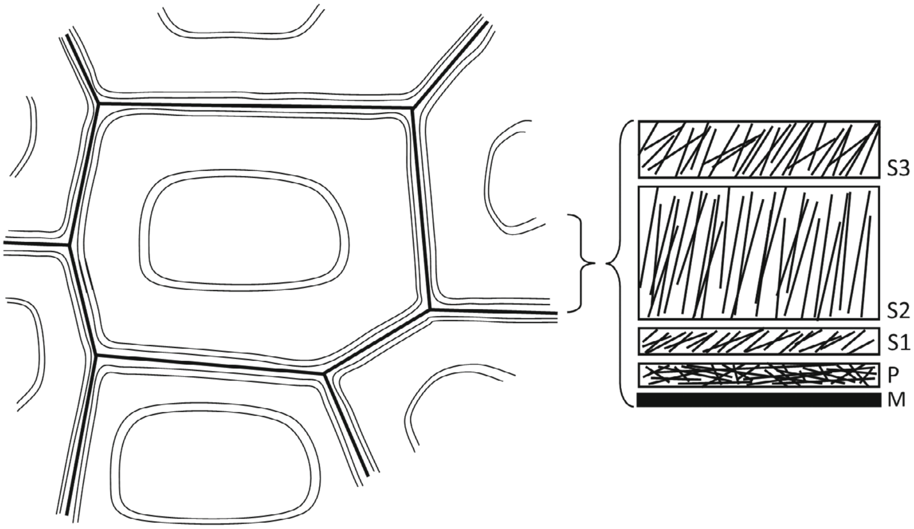

FIGURE 2 Structure of a plant cell wall.*Source*: Adapted with permission from Reference 15. Copyright 1938 American Chemical Society.

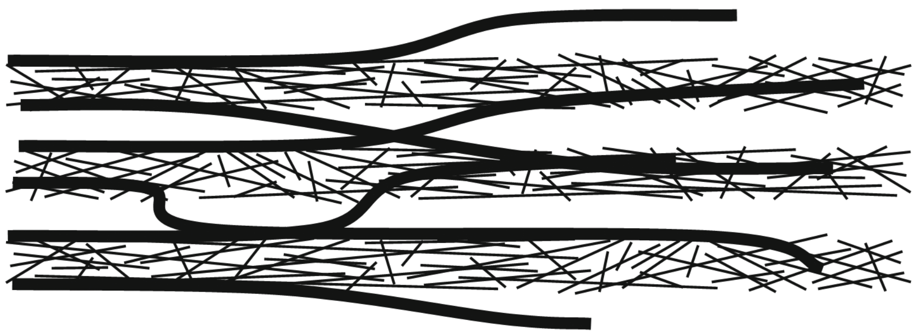

FIGURE 3 Structure of the primary wall. Hemicellulose links randomly oriented microfibrils.*Source*: Adapted with permission from Reference 16. Copyright 1990 Springer Nature.

The cell wall can be considered as a network of polymer molecules that overlap and interact with each other. The interactions between a large numbers of different cells generate several emergent properties in the wood and build highly complex dynamical structures. The arrangement of the polymers and the interactions among them are responsible for most of its physical and chemical properties. Cellulose microfibrils are arranged in a matrix of hemicellulose that serve as linkers between the fibrils (see Figure 3) Covalent bonds are present between the polymers, leading to linkage of the hemicellulose and the microfibrils.[16] This scaffold serves as a template for lignin formation.[14,17] However, there are not only interactions between the matrix molecules and the microfibrils, but also between the matrix components themselves.

The characteristics of wood are determined by the properties and arrangement of various polymers, which are influenced by different factors such as the structures of the polymers, including varying base monomers, chain lengths, and degrees of polymerization, as well as the variable distribution of the polymers within the structure. Other factors that contribute to the characteristics of wood include cell types (such as vessels and fibers), the thickness and individual layers of the cell wall, and the degree and type of lignification.[17–19] Depending on the polymer, the structure forms elliptical pores of different sizes, and depending on their size and shape, the formation of lignin is restricted.[19] In particular, the orientation of the polymers within the cell has a decisive influence. This applies to both the orientation of the cellulose microfibrils within the cell wall and the orientation of the hemicellulose in relation to the fibrils.

The primary wall consists of randomly arranged microfibrils. S1 is a thin layer with a rather disordered orientation of microfibrils with a large angle between the microfibrils (50°–70°). S2 is much thicker and has the greatest influence on the macroscopic properties of the cells. The fibrils are more orientated than in S1 (angle 5°–30°).[14] Within S2, the lignin content correlates with the microfibril angle. The higher the angle, the higher the lignin content.[20] S3, on the other hand, is again thinner and, similar to S1, exhibits a disordered arrangement of the fibrils (microfibril angle <70°). S3 has the lowest concentration of lignin in the structure and is responsible for water transport within the cells. Lignin is a hydrophobic polymer, which would restrict transport at higher contents.[14] The cell is able to react to mechanical influences, for example, cell growth, or external influences from the environment by changing the distribution. The inner layers S3 and partly S2 are able to replace the soft lignin with crystalline cellulose. In addition, mechanical stress can cause interactions between the cellulose fibrils to result in increased order, or a more aligned orientation. The parallel orientation of fibrils relative to the fiber is also critical to its strength. Depending on the wood species, the cell walls form different orientations of the cellulose skeleton, which can produce a higher degree of order through cell growth.[17]

7 | ARTIFICIAL INTELLIGENCE IN ARCHITECTURE, ENGINEERING AND CONSTRUCTION (AEC)

While the aforementioned processes of self-organization can be observed in nature, similar scenarios are also present in artificially produced environments. With specific regard to tasks and operations in the construction industry, several application areas can be discussed. Self-organization processes already exist, not only in the fields of designing, planning and execution, but also during the actual use of buildings, for example, in smart homes, smart factories or even in structures like bridges or dams. Since computer-controlled sequences constantly increase in number, it is useful to show that there are similarities between natural and artificial processes. In order to demonstrate the potentials associated with new and innovative developments, the following sections are illustrating AI-based scenarios to consider the possibilities of self-organized systems. The main focus of these considerations is primarily on construction sites, which are becoming increasingly digitalized. Considering heterogeneous robotic systems is also important—often because there are better and faster ways for a machine to solve a specific problem than to imitate how humans would approach it. With a glance back at the previously listed aspects of self-organization processes, some of these aspects are illustrated with examples of *reinforcement learning*.

Since the term *artificial intelligence* (AI) is often interpreted in different ways, a more practical and AEC-related definition will be applied here. In regard to the content of this paper, AI can be seen as a process of programming computers or engineering machines, especially to perform tasks that require *intelligence*.[21,22] To achieve such intelligence, programs and machines must be trained for specific tasks. In the field of machine learning—which is generally regarded as a subfield of AI—three main methods are eligible for this purpose: *supervised learning*, *unsupervised learning*, and *reinforcement learning*.[23] The latter, in particular, can be used in conjunction with self-organization processes, which will be explained in more detail below, especially with regard to CPS in the construction industry. Artificial intelligence also encompasses a range of different and often newly developed methods. Boden distinguishes a total of five main types: *symbolic AI*, *neural networks (connectionism)*, *cellular automata*, *dynamical systems* and *evolutionary programming*.[23] All of these types are also relevant to the AEC industry. However, the focus of the following sections lies primarily on evolutionary learning.

8 | DEEP LEARNING FOR PROCESSES ON CONSTRUCTION SITES

Agents learn a certain strategy based on rewards, but also on punishment. Like in biological processes, different feedback messages are shared to tell agents in a system what was done well or what could be improved. Reinforcement learning can, therefore, also be seen as *learning with a critic*. In such a reward system, agents can also take a sequence of actions and receive feedback only at the very end of multiple steps. Regardless of when a response is given, agents should learn to generate the actions to maximize the reward in later trials. It has to be the agent itself that actively generates information by trying actions in the environment and receiving positive or negative feedback. If, for example, a robot on a construction site is able to try several behaviors, it could reinforce its single steps until one task is completed. In this regard, agents can be seen as *stand-alone decision makers*.[21] So even if reinforcement learning in itself is conditioned and biology-inspired,[22,23] there are concepts to use these approaches for artificial environments.

However, in order to transfer these thoughts to future construction sites, some further precautions need to be taken. For example, a robot that is designed to transport materials on site—regardless of whether it is moving on tires, crawler tracks or legs—should know beforehand all the project-specific dimensions such as weights, transport options and routes. Since this is not only very time-consuming, but also computationally demanding, it is more reasonable to use self-organized concepts in which a robot can decide ad hoc how to transport the materials.

As an example for a specific reinforcement case, imagine an agent such as a robot placing bricks to erect a wall. When the robot receives data, for example, the element type or an exact position for a brick, it can place each element one after another until the structure is completed. A common problem on construction sites is wind interrupting a task so a brick cannot be placed correctly. Here, it is important that the robot *knows* what to do next.

With the help of additional information, the robot can use data from other cases when a brick could not be placed correctly. In this case, the bricklaying robot benefits from a general data base—regardless whether it is an open or an proprietary source. Furthermore, the information from this specific example can now be stored into the database as well. This means that all relevant information, for example, robot type, brick type, weather condition, etc. can be stored, so that similar tasks on other construction sites can also benefit from this pool of knowledge.

To be sure that other machines are able to erect a wall without interruptions, it is important that all processes are evaluated. Without any feedback—regardless if it comes from a human or a machine—the system itself cannot learn. Therefore, reinforcement learning relies always on the combination of gaining and verifying data.

The *self* in self-organization also refers to a state of an individual agent in a CAS. A robot for example follows its own rules, and uses its own features in applying those.[2] It will be discussed later how this can also be implemented in a swarm-like system. Before that, we are going to show that self-organization processes and evolutionary learning also play a major role in applications in the AEC industry.

Evolutionary processes with constant feedback loops can also be described as *morphogenesis*, where organisms form great complexity from simple roots.[24] In the construction industry this may be used for the design of buildings inspired by natural forms, for example, to find the perfect shape for a façade. It is also worth mentioning that specific attempts have been made to implement other biology-inspired self-organization processes into artificial environments, for example, through *evolutionary programming, adaptation*, *metabolism*, *motor behavior*, *genetic algorithms* or *imitation learning*.[22,23] The main focus of the following considerations, however, is on machine learning.

Today, machine learning is a common method to teach machines how to discover patterns hidden in large data and realize data-driven predictions on future tasks.[25] To use the benefits of machine and reinforcement learning for construction sites, there needs to be a more versatile approach, for example, with *deep learning*. Since machine learning can simply be seen as a system that has been trained with examples or that recognizes patterns on the specific data, deep learning methods are used to train models with several levels of abstraction from a raw input to an output.[21] Deep learning is based on multilayer networks that recognize regularities in the input data at various hierarchical levels. In other words, deep learning represents a multilevel knowledge.[23] The many layers of a network can be seen as sublayers with subgoals, and therefore, as subsystems in a complex system, as shown in Figure 1. The importance of such a *system view* for tasks on construction sites will be shown in the next section. Before that, we are going to mention that this view can also be interpreted as a CAS.

With regard to complex processes on building sites, it is useful to approach new concepts with the help of *artificial neural networks* (ANN), which are highly simplified models of biological neurons.[22,24] For example, it is important to consider that construction tasks are often interwoven with other processes on site. While building a structure, it is, therefore, not only necessary to see the single operations on the spot, but also in a more interacting context, for example, with different work phases or different disciplines, like masonry, carpentry, or window installing. If we see construction sites with the aspects mentioned before, it is also feasible to talk of a CAS, a system of agents, which interact among themselves and/or their environment. The environment is a key aspect here, because every construction site is different. When it comes to CAS, system views usually refer to processes in nature and society[2]—technological aspects are often not included. If we change the perspective to a more technical view, CAS can also be seen as CPS.

9 | CONSTRUCTION SITES AS CYBER-PHYSICAL SYSTEMS

Since construction sites will increasingly develop more and more into CPS, it is extremely helpful to consider digitally supported manufacturing processes in the context of self-organization. Various aspects that are important in the context of artificial processes also exist in CPS. In many cases, these systems are organized as a network to handle a task in a collaborative manner, especially to show a purposeful behavior.[21,26] With this description of a CPS, the connection to the aforementioned self-organized processes can be established.

The first connections between natural and CPS were made in the mid-20th century. Scientists brought together cybernetic ideas with self-organizing concepts and feedback.[23] The *cyberneticians* often drew inspiration from control engineering and defined systems where changes follow simple rules depending on the current state of neighboring units, for example, with circular coupled machines.[27]

Looking at the agents situated in CPS, they must not only have the capability to communicate with other units or with their environment, they also need to be mobile. Thus, a robot—just like a living insect—should be able to move around, avoid collisions with static obstacles and safely get out of the way of other moving objects, simply by sensing them. Communication is, therefore, another main aspect for a functioning system: Without input from other agents, a single robot is not able to execute complex tasks. However, especially in defined environments, they can work together by showing altruistic behavior.[23] Associated with cooperative actions, it is possible to transfer these concepts to artificial systems or CPS. In this respect, the term *evolutionary robotics* is more than reasonable. This specific view can represent a way of designing robots while using automated processes to create innovative robot designs.[22] For construction sites, this is important because different tasks have to be fulfilled by different agents.

In order to design specific machines for the diverse tasks on construction sites, it is necessary to consider different steps. For example, Winfield describes evolutionary robotics with four stations: 1. *fitness evaluation*, 2. *selection*, 3. *mutation (crossover)*, 4. *replacing*.[22] With regard to these steps, evolutionary robots can result from a combination of engineering and random variation. The agents evolve unpredictably, not carefully designed. Evolutionary learning lies within these processes, in which multiple generations of robots can be engineered for constantly changing CPS.[22,23] Robot learning cannot only be described as evolutionary learning, it is also inherent in the aforementioned reinforcement learning. As easy as the connections may sound, more aspects have to be considered.

In general, robots in unpredictable environments or changing surroundings are perhaps quintessential examples of AI itself. In the absence of a critic who can observe all ongoing processes, evolutionary AI needs more than a monitoring quality-rating system like in reinforcement learning. Regarding the exchange of various information between different robots, the communication in constantly changing systems is an important factor. If agents had no common attributes for data exchange, there would be no correlated feedback among robots or machines, and then emergent properties would be impossible.[2]

With insights from self-organized collective intelligence, as demonstrated by termites or ants, we can rely on the research field of *swarm intelligence*. Robots in a swarm need to be able to coordinate their actions and work as a team. Such systems can be defined as *collective robotics* or *swarm robotic systems*, where multiple agents act as a group to achieve greater tasks.[22,23] Regardless of what such a complex structure is called, swarm intelligence can be used to engineer new systems.

As mentioned before, there are many different tasks to be fulfilled on construction sites. Thus, it is not only important for agents to communicate, but also for various robots to transfer relevant information from one agent to another. A cyber-physical network consisting of different robots can be defined as a *heterogeneous system*. Unlike agents in a homogenous network, where each robot is identical, heterogeneous systems have several types of robots, each with a distinct function.[2] This gives the overall system more flexibility to undertake a wider range of tasks, while retaining the robustness of the whole swarm.[22] For tasks on construction sites, these aspects are very important. Heterogeneous multi-robot systems are relevant for CPS, where semi-independent and self-assembling modules can be integrated into structure-specific concepts.[22] This is also relevant, because most of the time, the tasks on a construction site are connected to different processes, like geotechnics, masonry or tiling.

The described aspects can be viewed in two different ways: *agent-level adaptation* and *system-level adaptation*.[2] Applying both concepts to construction sites is important because in most cases, the robot's design will vary enormously over different applications and operating situations. But whether a robot moves on tracks, flies, or swims, it will always need a number of common subsystems. Thus, it is reasonable to see future construction sites as constantly changing systems with different layers. In this regard, deep learning algorithms are now the main aspect. Artificial neural networks are important in robotics and of special value for evolutionary robotics.[22]

Since some artificial systems are organized by hierarchical control with the described *stand-alone decision makers* and communication concepts, it is reasonable to use these approaches for systems with various sublevels and agents. Boden explains this idea with the example of a robot that has to take different steps: The goal of leaving a room may be designed to include the sub-goal of opening a door.[23] A hierarchical concept can, furthermore, be expanded to various other examples.

Particularly for construction site processes or complex tasks which are not programmed specifically in a system with sublevels, it is also possible for participants to act independently without level-based commands in a varied and diverse system. More precisely, there may be different types of robots on site, for example, for climbing stairs, jumping over trenches or carrying heavy material, which do not know their next step, but only a long-term given goal or destination. In such cases, it is also useful to apply self-organizing concepts without hierarchical command structures. In a concept like this there is "no central plan, no top-down influence, and no individual possessing *all* the relevant knowledge."[23] Goals are more difficult to achieve, simply because the point of view is embedded directly in the agents rather than in a supervised system.

From an engineering viewpoint, a swarm of robots with identical or even different agents lends itself to solving tasks on construction sites. Without a central control computer or a communication network for various robots, the planned processes can possibly not be executed adequately. This is a very important aspect when dealing with complex systems where one task must follow another rather than solving a problem with the same agents. Nonetheless, a swarm approach is attractive, mostly due to its scalability and robustness, but also because of its high-fault tolerance.[22]

Since the behavior of a robot is the result of its interactions with the world, *situated robotics* can be a reasonable approach for construction sites. Like decision makers in CPS, there is much potential for free-behaving robots, for example, in unpredictable environments. Due to various tasks on site, *situated construction robotics* must be heterogenous and interactive. CPS are also known as embedded systems[21] and swarm intelligence can likewise be considered cellular automata (CA), where the basic analogy is living cells cooperating in multicellular organisms.[23,24] In some cases, CPS also refer to *Artificial Intelligence of Things (AIoT)*, which incorporates AI techniques into infrastructures for more efficient operation and data analysis.[25] In such interconnected systems, physical devices like sensors, drones, and scanners, as well as mobile phones and tablets can be used to store and share relevant information. Since data for structures and buildings is now stored in digital models, it is reasonable to connect the physical elements with such models to control and monitor processes and tasks in construction projects. As shown in Figure 4, *building information modeling (BIM)* or *digital twins* can be used to manage different subsystems. The illustration displays an example of a system with various sublevels on a building site. Overall, three subsystems can be distinguished: *geotechnics*, *solid construction* and *interior fittings*.

Since all subsystems in Figure 4 are based on a digital twin and are also interconnected with each other, the concept can be seen as a coherent CPS. For example, subsystem II (*solid construction*) has two more levels and each of these levels can have different agents to fulfill specific tasks, which in turn are necessary for subsequent steps. In such a monitored or controlled system, the various robots, for example, a bricklaying or welding machine, can get relevant information from a central BIM model. Even without specific data from a digital twin for every single step, robots can also use computer vision or sensor technologies for self-organized actions. Particularly on construction sites, the ever-changing framework

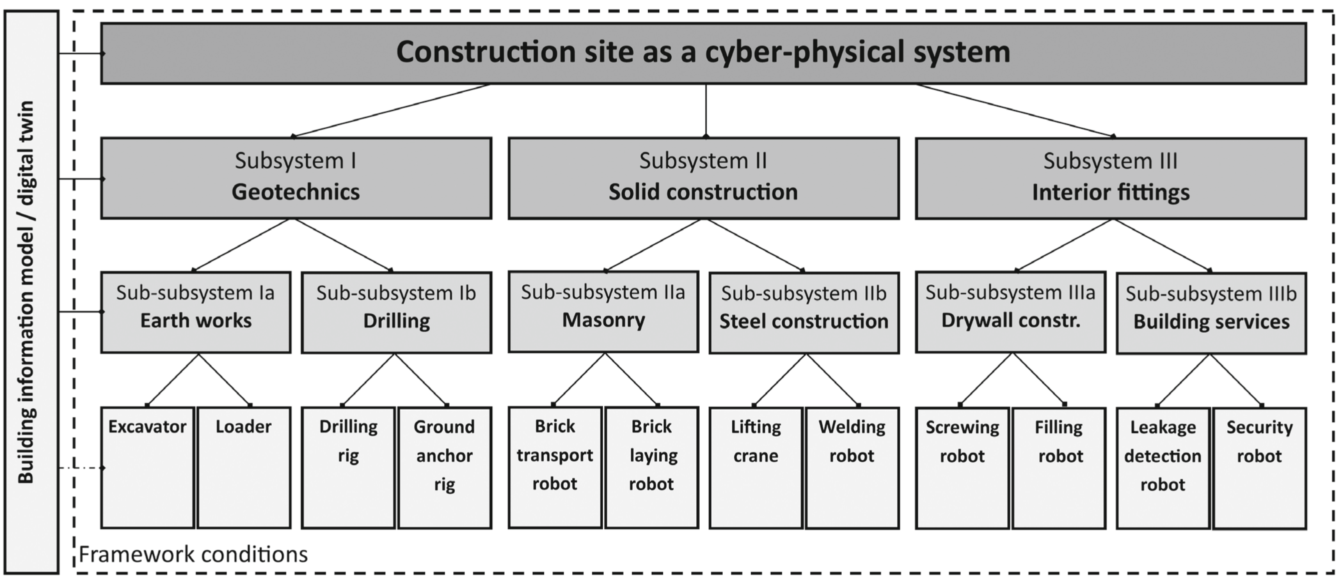

FIGURE 4 Construction site as a cyber-physical system with various subsystems.

conditions are the main aspects when it comes to stand-alone decisions. Here, a digital twin can also help to simulate how robots would act when they had to make independent decisions.

A specific example for self-organizing machines on a building site can be the construction of a slab for a house: After the placing of prefabricated concrete elements with a computer vision-controlled crane, the reinforcement bars have to be placed. Here, a wheeled robot can be put on top of the protruding steel of the slab.[28] Since the robot may also be able to use computer vision and is perhaps guided by geofencing on the unfinished area,[29] the next task is to lay the rebar elements in the specific place. For this, the data from a digital twin is used.

If the rebars are too long, two robots can collaborate or the construction crane can help to place the steel elements. Furthermore, another heterogenic robot fleet must be implemented to create the formwork for the concrete. In this example, it might be wooden plates on every open side of the slab. One or more robots have to keep the elements in position while other machines can drill or bolt the wooden plates into the walls underneath. All relevant information, for example, height of the formwork or position of the drilling holes, comes from a digital twin.

After fixing the formwork and putting every rebar in the correct position, the binding process can start. For this, a tying robot has to recognize the cross points to fix the rebars.[30] Here, the feedback inside the system is very important, because the binding of the single rebars is based on the recognition of the robot or on the computer vision system on site. For example, the shifting or displacing of the rebars must be considered, since the robot is moving on the steel mesh itself. Therefore, it is necessary for the system to react to incidents during these processes.

Before the pouring of the concrete can begin, the area inside the formwork has to be cleaned. Here, a robot can use an air pressure cleaner to remove remaining dust and small items. For the pouring process itself, another robot can pump concrete into the formwork. Again, feedback is necessary for the machine to know when to stop pouring the material. The next step for creating the slab in this example is the consolidation of the concrete. For this, one more robot in the heterogenic construction fleet can be applied to use a vibration device inside the fresh concrete. Here again, constant feedback is necessary, because the effects of the consolidation processes regarding the vibrations on the rebar mesh and the formwork must be considered.

At the end—if there is no screed layer on top of the concrete slab—the surface should also be smoothed out. Here, a concrete leveling robot can be used.[31] This machine—like all the other technical devices described before—is connected to the CV system of the construction site which generally relies on the information of the digital twin. During all the processes described in this short case study, a drone can furthermore check the correct positioning of the structure at any time[32] while the applied robots navigate with the help of cameras and LiDAR scanners inside the CPS. Also, all the collected data can be sent to the digital twin in real-time to show inconsistencies to compare the planned structure with the already built elements. With this constant feedback, the next steps can be determined.

Furthermore, enormous amounts of data can be shared through a CPS or a central network. In these cases, data exchange may be analyzed by various AI methods to gain insights for better supervision and decision making.[25] By synthesizing and analyzing data collected inside a cyber-physical infrastructure, digital twins can also automate real-time decision making at an operational level to remotely control a construction worksite. A CPS then provides a steady flow of time-series data, so synergies between CPS and BIM" will become a hot spot in future works."[25]

10 | APPLICATIONS IN AEC: CONSTRUCTION ROBOTS AND OTHER EXAMPLES

Already today, many AI examples can be found, in which robots are used on construction sites.[33–35] However, widespread application of digital or intelligent machines has only been observed in some occasional projects. Even though an adequate number of technologies are already very advanced, many of them lack practical realization; the existing approaches are often in early stages of only a few research projects. In order to provide an overview of the *status quo*, examples of intelligent CPS based on self-organizing processes that can be used in the construction industry are presented below.

One field of application is the planning of objects and structures. In the architectural and engineering field, it is already possible to use digital support, for example, with the help of computer programs like calculation or modeling software (FEM or BIM). With ongoing development, particularly in AI-based research, it is now even feasible to use methods like *conceptual design*, where different application areas are managed by algorithms for design ideas, morphogenesis, building shapes, and even design optimization.[36] For example, it is possible to apply intelligent concepts, in which knowledge discovery and decision making can be used in adaptive elements like façades.[37,38] As implied with these potentials, it is obligatory to use BIM models and digital twins with an outlook on smart homes and smart cities, particularly in the early stages of planning processes. Moreover, with increasing options, it is possible to create much more advanced systems for higher levels of automation, interoperability, and intelligence. Besides the aforementioned fields, the concept of *generative design*—which is essentially based on deep learning—provides more approaches, for example, for use in design processes like calculations and verifications, cost estimations, or even structural, bioclimatic, acoustic, and lighting design.[24,39] Even *Natural Language Processing* (NLP) can be used to deeply investigate lots of text files, for example, for safety reports or for evolutionary algorithms with automatic and optimal rebar layout in reinforced concrete structures.[40,41]

Artificial intelligence and self-organizing processes are also helpful when it comes to tasks on site. As explained before, it is possible to use different robots as agents in CPS. Examples for adaptive robotic manufacturing using higher-order knowledge systems include brick layout systems for masonry walls or robotic assembly concepts for timber joints.[42–45] Even 3D printing can be combined with intelligent behavior, for example, in transforming configurations for self-assembly and self-repair.[25] For navigation tasks, which are very important on construction sites, agents may use *simultaneous localization and mapping* (SLAM), where robots can navigate through unknown territory. It is also worth following developments in more applications of construction automation for optimized site planning or for logistics on site, for example, building cranes that can automatically detect objects.[24,46,47]

Another promising field of application for self-organizing processes is vision-based monitoring of construction sites.[48] For object detection, the connection between computer vision and evolutionary robotics is of great importance.[49,50] For example, neural networks can be used to inspect construction sites with an unmanned aerial system.[51] Inspections are also applicable in other fields, for example, for automated real-time damage detections, for localizing cracks, or for finding bug- or pinholes in concrete or masonry structures.[47,52–55] Another practical example is areas to which humans have difficult or no access at all, such as derelict buildings or underground sewer pipes.[56] Furthermore, real-time rebar counting[57] or repair tasks come to mind.[58]

When planned structures are completed, there are even more applications for artificial self-organizing concepts, mainly with regard to facility management processes. Here, in conjunction with digital twins or inside smart cities, evolutionary methods can be used to generate neural networks that predict energy consumption.[38] Furthermore, AI concepts can be applied for infrastructure maintenance or building management, but also for virtual feedback support systems that can help instructors and trainees to receive feedback, for example, for complex training sequences.[25,59]

Table 1 shows some examples for the use of artificial intelligence in the construction industry. The overview contains various cases in different fields of the building sector. The table summarizes some of the ideas proposed in this paper, particularly self-organization regarding building materials and construction sites.

TABLE 1 Examples of complex adaptive systems in various fields in the construction industry.

Complex adaptive systems	Fields in AEC	Processes and devices	Self-organization and artificial intelligence
Without specific agents	Building materials[a]	Often natural processes, for example, hydration, distribution, or pressure	Part of evolutionary learning and natural adaption
	Designing Planning Managing	Use of various software and algorithms, for example, to create digital models for virtual and augmented reality	Conceptual design, generative design (e.g., based on reinforcement learning)
With artificial agents	On-site construction[a]	Robots, for example, humanoids, 3D printers, or wheeled robots	Cyber-physical systems, artificial internet of things (AIoT)
Agents possible	Smart Cities	Logistics, facility management and smart grids with software and robots	Artificial internet of things (AIoT) (e.g., based on reinforcement learning)
	Monitoring Refurbishing	Computer Vision and SLAM, for example, with digital twins, sensors, drones, and scanners	Supervised learning, Reinforcement learning

[a]Contents of this paper.

By using artificial intelligence as the backbone of future construction projects, a lot of opportunities arise. Therefore, the continuous application of AI methods helps increase productivity,[25] decrease costs[24] or reduce energy consumption.[38] Furthermore, it is very helpful to take advantage of the opportunities associated with digital twins. Simulations can contribute to more efficient and sustainable modeling processes or optimized project performance, for example, with simulations for various building or structure modifications to predict future conditions for maintenance planning. In this regard, deep neural networks can be seen as "a revolution in the construction field."[47]

11 | CONCLUSION AND OUTLOOK

The overview of self-organizing options in this article has shown that there are many possibilities for applications in AEC. Therefore, the connections between evolutionary systems and artificial intelligence can help to understand basic aspects, but also to implement them in future projects based on natural concepts. With the example of a construction site as a CPS, we could demonstrate that the definition of self-organization can be applied to man-made processes: The order is established by local interactions of individual components (e.g., robots) that create structures on a global scale (e.g., a planned structure). The system requires an external energy source (e.g., supply for the machines on site); without one, order (e.g., planned schedules) cannot be maintained. Order is an interaction of internal and external influences. External influences (e.g., weather conditions) can initiate a structural transformation, but cannot set the direction. Furthermore, self-organization is a time-dependent process that responds dynamically to change. It is an interplay of internal feedback loops at multiple levels (e.g., subsystems in Figures 1 and 4). Nonlinearity allows for flexible adaptation and the generation of complex emergent properties (e.g., evolutionary robots). The boundary of the system (e.g., execution plan) must be defined.

However, with regard to a fundamental basis for science and business, it is helpful to find common terms, so processes in AEC become more autonomous in the future. Definitions of *self-organization*, *emergence*, *feedback* or *reinforcement learning* specifically applicable to the construction industry can, therefore, help to clarify basic standards. A focus on more technical processes in AEC may also help to counteract the shortage of skilled workers or reduce accidents on site.

Beside the core findings of this paper, it must be concluded from concepts of self-organization in materials science, project management and construction that autonomous systems generally have to be *heterogeneous* and *communicative*, but also *situative*, particularly when dealing with constantly changing environments. In addition to agent- and system-level adaptations on construction sites—usually managed with a digital twin that serves as a manager for different agents—, it is important that processes and interactions in AEC are becoming more dynamic, both between agents themselves and between agents and their surroundings.

To implement concepts of self-organization in the construction industry, many challenges must be considered. For future projects, it is important to focus on interactions and communications—not only between humans and machines, but also between heterogeneous robot types. In this regard, it is relevant to do research in fields of data exchange and interfaces. Here, progress can only be made if more data is collected over the next years and decades. Without sufficient information, the proposed concepts of self-organization cannot be realized. Furthermore, advancements must be made with regard to the mobility of machines. The increase of robots on site entails the energy problem that should always be considered, particularly because of the climate crisis we are facing.

All these obstacles make it difficult to give a precise outlook on future trends in the construction industry. A specific road map is hard to define, since various topics are still in early phases of development. For example, it is not determinable whether projects are based on concepts that involve heterogeneous machines or swarm robotics. It is also not clear when construction sites are becoming more autonomous, since human-machine interactions are still mandatory in the next years. Even if there are more CPS in the future, making a prediction is complex because of the developments in evolutionary robotics with stand-alone decision makers and because of the application of supervised systems with different sublevels.

Another crucial aspect is data collection: Without reliable information from various case studies, the implementation of concepts based on artificial intelligence and machine learning will not be realized soon. Still, with the increasing use of digital models in the sector, and with new generations of participants using innovative concepts and devises, the outlook remains promising—even if the industry is still facing many challenges, for example, the shortage of skilled workers or the different framework conditions that come with every new project.

AUTHOR CONTRIBUTIONS

Jessica Lohmann: Conceptualization (equal); funding acquisition (lead); visualization (equal); writing – original draft (equal); writing – review and editing (equal). **Thomas Kölzer:** Conceptualization (equal); visualization (equal); writing – original draft (equal); writing – review and editing (equal). **Gunnar Schaan:** Visualization (equal); writing – review and editing (equal). **Frank Schmidt-Döhl:** Conceptualization (equal); supervision (equal); writing – review and editing (equal).

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CONFLICT OF INTEREST

All authors declare that they have no conflicts of interest.

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DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

ORCID

Jessica Lohmann https://orcid.org/0000-0002-0116-0490

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