Towards Multiagent-Based Simulation of Knowledge Management in Teams

Ingo J. Timm[1], Jan Ole Berndt[1], Lukas Reuter[1],
Thomas Ellwart[2], Conny H. Antoni[3], Anna-Sophie Ulfert[2]

[1]Business Informatics 1,
Trier University, Behringstraße 21, 54296 Trier, Germany
[2]Business Psychology, [3]Work, Industrial and Organizational Psychology
Trier University, Universitätsring 15, 54296 Trier, Germany
{itimm,berndt,reuter,ellwart,antoni,ulfert}@uni-trier.de

Abstract. Today's digital workplaces are characterized by an increase in the amount of required knowledge as well as available information for teams of co-workers. Hence, the question arises: Which knowledge is necessary for team members to effectively and efficiently conduct their tasks in a given work context? To support the design and management of flexible teamwork, this paper integrates perspectives from psychology and business informatics into a multiagent-based simulation model for analyzing and optimizing knowledge practices. It uses the well-known job-shop-scheduling problem as a foundation to simulate the effects of generalist and specialist knowledge structures in teams. The results of the evaluation show that this approach is suitable for reproducing psychological findings about the effects of these structures on a team's work performance. This motivates a discussion of the capabilities and current shortcomings of that simulation model. From that discussion, the paper derives a research agenda for extending the presented approach to a method for designing, analyzing, and optimizing real-world knowledge management strategies of human teams.

Keywords: Knowledge management, Team cognitions, Multiagent-based simulation, Optimization, Job-shop-scheduling

1 Introduction

Today's workplaces are characterized by a high degree of flexibility. This corresponds with an increase in the amount of required knowledge as well as available information [12]. This is particularly the case for digitalized workplaces in a variety of domains ranging from administration to modern production processes as in Industry 4.0 [21]. This poses a challenge for the design and management of knowledge practices. Since work processes frequently several steps which require different capabilities, developing structures and interactions within teams of co-workers is an essential task for this knowledge management. The key question is: Which knowledge is necessary for particular team members in order to enable effective and efficient teamwork for conducting specific tasks in a given work context? An answer to this question is an important prerequisite for both organizing flexible workflows and for developing new solutions to support them; e.g., by means of digital devices and assistance systems.

In order to facilitate the design and management of flexible teamwork processes, it is necessary to thoroughly understand knowledge practices in teams as well as to make them accessible to analysis and optimization techniques. For one thing, theories and studies in business and organizational psychology provide insights into those practices [16,7,9,26]. They focus on the effects of knowledge being shared or divided between team members (i.e., generalists or specialists) on the work performance and mental capacities of the whole team. Thus, they provide a solid foundation for modeling and analyzing knowledge management strategies in teamwork. For another thing, business informatics can complement this with methods for simulating and optimizing processes [20,1]. In particular, *agent-based modeling* and *multiagent-based simulation* have successfully been applied to the design and evaluation of novel approaches to flexible distributed task processing and cooperative problem-solving [8,22,35,3]. Consequently, bringing both of these perspectives together can open up new opportunities for developing simulations of human teamwork practices as a method for designing and evaluating flexible knowledge management strategies.

To the aforementioned end, this paper presents a multiagent-based approach to model knowledge in teams and to simulate the effects of different knowledge management strategies on a team's work performance. It integrates psychological findings about the role of knowledge structure in human teams with formalization, modeling, and simulation methods from business informatics in an interdisciplinary perspective. In particular, it maps the psychological concept of *team cognitions* to the well-established job-shop-scheduling problem. This facilitates the evaluation of team knowledge structures within the spectrum of specialist versus generalist teams by transferring knowledge management tasks to a formal optimization problem. The paper shows that the job-shop-scheduling problem can be an experimental setting for reproducing the effects of team cognitions in a multiagent-based simulation. In addition, it discusses potential extensions to that setting and the participating agents to better represent psychological notions of teamwork and knowledge within teams. Hence, it provides a first step to develop multiagent-based simulation as a method for designing and evaluating modern work processes in dynamic and complex environments (e.g., in Industry 4.0). In that context, it supports the vision of both creating a psychologically grounded simulation approach for such processes and making that simulation available to psychologists to complement classic methods like laboratory experiments and field studies about teamwork among humans [5].

The remainder of this paper is structured as follows. First, Section 2 introduces the foundations of knowledge structures in teams from the perspectives of organizational psychology and business informatics. It discusses the relations of both perspectives and points out research challenges which motivate their integration in an interdisciplinary approach. Subsequently, Section 3 transfers those foundations to the job-shop-scheduling problem in order to formalize knowledge generalization and specialization in teams. This provides the basis for developing and evaluating a multiagent-based simulation model in Section 4. That section presents and discusses simulation results which show the appropriateness of job-shop-scheduling for evaluating and optimizing knowledge management strategies in teams. Moreover, it proposes extensions to the model for a more detailed integration of psychological concepts. Finally, Section 5 concludes on the findings of this paper and outlines the next steps toward the aforementioned vision.

2 Knowledge structures in Teams: Foundations and Challenges

In order to facilitate successful teamwork, it is crucial to consider and manage task-specific knowledge of teams. In this context, *knowledge* refers to the required abilities and skills as well as to the availability of information to conduct particular tasks. Such knowledge can either be shared among the team members (generalist) or it can be divided between them (specialist). This distribution or division of knowledge in teams affects both functional and dysfunctional processes such as their task-processing efficiency coordination, information overload, or their resilience against disturbances [41,9]. While *specialist* (divided) knowledge can enhance the efficiency by division of labor, *generalist* (shared) knowledge increases a team's ability to cope with disturbances by means of redundant capabilities.

As an example, team members in personnel administration can specialize on specific tasks like salary accounting, the management of applications, or the processing of sick reports. In large organizations, this specialization allows for efficient workflows and reduces the load of required information for the individual team members. They can concentrate on particular segments of the overall administration process and develop routines for their tasks. Nevertheless, this makes the team members largely irreplaceable in case of illness, occupational change, or retirement. Consequently, it becomes necessary to share a certain amount of knowledge within a specialized team in order to ensure its robustness. This is especially crucial for teamwork in different fields such as health care, public safety, and even logistics in a globalized world. However, the generalization of team knowledge comes at the cost of increased information loads, coordination overheads, and context changes between tasks which reduce a team's efficiency. Thus, the challenge of managing knowledge for teams is to reach an optimal context and task-specific balance between specialization and generalization.

In order to address the mentioned challenge, this paper develops a method for dynamically analyzing the effects of knowledge structures in teams. To that end, it adopts an interdisciplinary perspective on teamwork which combines *psychological* insights into team cognitions with modeling and simulation techniques from *business informatics*. Hence, the following subsections first present the foundations for this approach from the perspectives of those disciplines and then discuss the challenges for integrating them in a common framework.

2.1 The Psychological Perspective: Team Cognitions

From a psychological perspective, teams are collective information-processing systems [16]. Team members memorize knowledge required for their tasks, they specialize on particular areas of expertise, or they share knowledge and information with each other [24,10]. These various approaches to the organization of team knowledge are known as *team cognitions* [34]. Team cognitions describe the structure in which knowledge important to team functioning is mentally organized, represented, and distributed within the team and allows team member to anticipate and execute actions [7,9]. Therefore, they are particularly suitable as a theoretical concept for describing, modeling, and analyzing knowledge configuration approaches in collaborative work processes. Team cognition, as an emergent state, are conceptualized as (1) shared team knowledge or (2) distributed team knowledge [9].

When working together, it is important for team members to share their knowledge about task and team relevant information with each other in the form of *team mental models* to facilitate successful cooperation and coordination [7,9]. On the one hand, this generates trust and increases coordination and the robustness of the work process against disturbances by means of information exchange and the acquisition of group knowledge [43,26]. On the other hand, sharing of the entire knowledge among all team members results in an increased amount of information that needs to be processed by each individual which can lead to information overload [11,12]. Information overload endangers the effectiveness and efficiency of the team as its members struggle to focus on specific current tasks when constantly switching between different contexts [9].

Contrastingly, specializing on particular areas of competence reduces the cognitive load faced by members of a team [17]. That is, each team member can focus on her specific expertise which reduces the load of information being processed. This distribution of knowledge in specialized teams increases the overall knowledge capacity of the whole team since individual members only have to memorize and process information which is relevant to their areas of expertise [18]. However, this potentially makes the team as a system more fragile as it lacks the required redundancy of knowledge to avoid confusion, conflicts, and failures [41].

In fact, a completely specialized team will be dysfunctional. This is because effective coordination between its members requires them to have some meta-knowledge about their co-workers' competencies and the overall process of collaboration. Such a *transactive memory* provides a shared context for the performance of divided tasks [10]. It contains knowledge about the location of expertise (*knowing who knows what*) which facilitates cooperation, coordination, and further specialization [18]. Moreover, a transactive memory even increases both a team's performance in dynamic environments and its ability to include new members [32,29]. Consequently, the organization of team knowledge structures consisting of both shared as well as distributed memory is crucially important for the successful design of teamwork processes. However, the challenge is to find an optimal balance between generalist and specialist team cognitions with an appropriate transactive memory depending on the context, structure, and environment of the tasks (see Fig. 1). In order to achieve this, the following sections propose an interdisciplinary research approach combining psychological theory and studies with methods from business informatics.

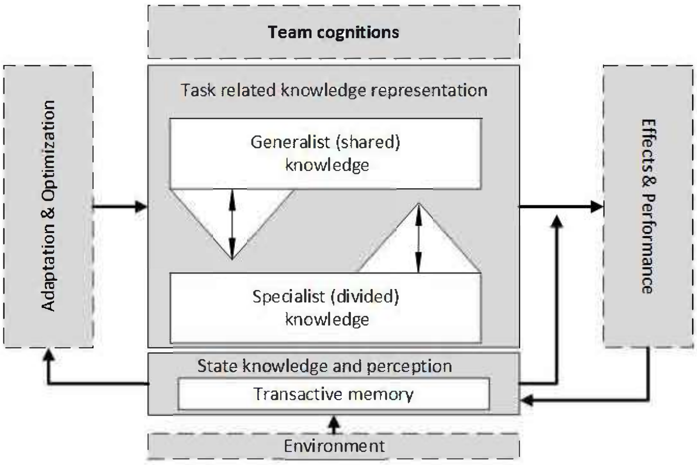

Fig. 1. Optimizing teamwork by balancing knowledge structures

2.2 The Business Informatics Perspective: Multiagent Systems

From a business informatics perspective, representation and distribution of knowledge can be modeled and analyzed by means of *multiagent systems* (MAS) [45,40,31]. As an approach to distributed artificial intelligence, MAS apply decentralized solution strategies to complex computational problems [42]. To that end, MAS utilize software agents which autonomously fulfill different tasks and coordinate their distributed activities. These agents process knowledge in their decision-making and exchange it in their coordination efforts [13,44]. Hence, the problem of optimizing distributed problem-solving in MAS resembles the challenge of identifying and applying appropriate team cognitions among humans.

Indeed, the question of balancing generalization and specialization of knowledge also arises in MAS research. Artificial agents frequently use formal *ontologies* for both their knowledge bases and their communication [2]. In order to successfully coordinate their activities, they require a certain amount of shared knowledge (i.e., shared ontologies) to achieve mutual understanding of the communication contents [37]. Furthermore, redundant problem-solving capabilities increase the robustness of MAS by enabling dynamic compensations of failures by alternative agents [8,22]. Nevertheless, it is undesirable to provide every agent with all available knowledge since specialized agents can often solve their tasks more efficiently which, in turn, affects the efficiency of the whole MAS [35,15].

In order to organize distributed problem-solving efforts of artificial agents, a wide variety of structuring approaches for MAS has been proposed. These techniques draw inspiration from cooperation processes among humans by defining multiagent organizations in terms of particular roles and channels of communication between those roles [19]. They range from rigid *hierarchies* and more flexible *holarchies* to dynamically established *teams* for particular tasks [19,14,33,46,35]. In multiagent organizations, a role specifies the necessary capabilities for an agent to collaborate successfully with other agents. In addition, the channels of communication denote the possibilities and requirements for knowledge transfer between the agents. Selecting an appropriate organizational structure is, therefore, crucial for effective and efficient multiagent coordination, particularly in dynamic environments [3]. Thus, similar to the findings in psychology, MAS researchers also have identified the need for a certain amount of meta-knowledge about teamwork processes. In order to successfully work together, agents must be able to reason about the capabilities of their counterparts and to integrate them into an appropriate organizational structure for the tasks at hand [39,28]. This leads to the challenge of identifying the required meta-knowledge and providing it to the agents to facilitate their coordination.

2.3 Challenges and Opportunities: An Interdisciplinary Perspective

As the preceding subsections have shown, organizing roles and processes in teamwork plays an important role in psychology as well as business informatics. Researchers of both disciplines face the question of how knowledge should be shared or divided among team members to allow for optimal collaboration. Consequently, this paper adopts an interdisciplinary perspective in which the disciplines complement each other to cope with that challenge and to develop a common understanding of distributed work processes.

In that context, psychologists can utilize methods from business informatics (e.g., ontologies) to formalize generalist and specialist team cognitions. This will open up new research possibilities for analyzing teamwork at an organizational level, at which collaboration not only occurs within teams but teams also interact with each other in a *multiteam system*. Such large-scale settings are difficult to cover in classic laboratory experiments or field studies [47]. This problem can be overcome by combining these methods with computer simulation studies [5].

In business informatics, agent-based simulation is a well-established technique for evaluating system designs before implementing new control strategies or constructing physical facilities [20,23]. Given the aforementioned formalization of team cognitions, such an approach can also be utilized in organizational psychology for developing theories as well as for designing experiments and studies [36]. In turn, MAS researchers can profit from these formalizations and simulations as they provide deeper insights into the design of distributed processes and inspire new developments of cognitive architectures for engineering intelligent artificial agents. While such architectures have been adopted by MAS researchers, they are rarely applied to agent-based social simulations [30,6]. This limits the latter's usefulness for explaining human behavior [38]. If social simulation models can be enhanced with cognitive agent architectures, they will provide new techniques for designing complex human-machine interactions in future production and logistics processes (Industry 4.0) [21].

As a first step towards that vision, a formal setting for analyzing and simulating collaborative work processes is required. That setting must be capable of representing the spectrum of knowledge organization approaches between generalization and specialization. This will allow for comparing different team cognitions according to their performance in various task scenarios. To that end, the remainder of this paper proposes the well-established job-shop-scheduling problem as a foundation for developing and formalizing these scenarios. Thus, the following sections describe that setting in the context of team cognitions, evaluate its appropriateness for simulating the effects of generalist versus specialist teams, and identify the required further steps to develop an interdisciplinary approach for simulation-based analyses of knowledge management in teams.

3 Formalizing Team Cognitions: A Job-Shop-Scheduling approach

Before simulating team cognitions, teams need to be formalized, which includes a formal representation of team members and their knowledge. Therefore, this paper introduces a model based on a job-shop-scheduling approach. The job-shop-scheduling problem is a well-established problem formalization in the area of production processes and describes the scheduling of jobs to machines [1]. Similar to human teams, in which team members produce an output by processing information, the machines process tasks to finish jobs. In order to map the requirements of modeling team cognitions, the job-shop-scheduling is defined as follows [1,4]:

- Let $J = \{j_1, ..., j_n\}$ be a finite set of jobs
- Let $M = \{m_1, ..., m_n\}$ be a finite set of machines
- Each Job j_i consists of a finite subset of tasks $T_i = \{t_1, ..., t_n\}$
- Every task t_i has to be processed in a predefined order by the designated machine
- Each task t_i needs a predefined processtime p_i

The scheduling itself is described as an assignment of tasks t_i to machines m_j, with the aim of optimizing the output which can be defined as ,e.g., the overall makespan. The key requirement for this task allocation is knowing which jobs need to be done and which machines can process them. In fact, different machine configurations can be used to present different knowledge structures in teams. Therefore, job-shop-scheduling is an interesting setting to analyze different team configurations in an agent-based model as depicted in Fig. 2.

Each machine represents a team member and all machines together describe a whole team. A machine is able to process a predefined set of tasks, which is

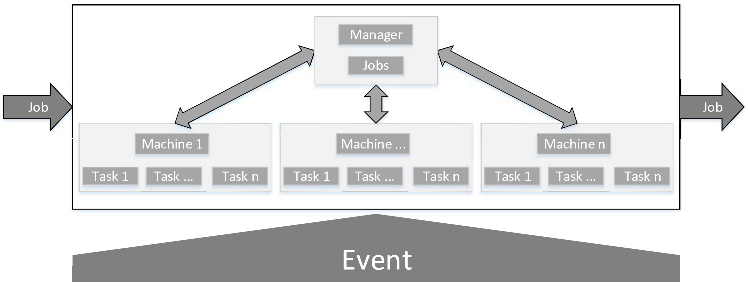

Fig. 2. Modeling knowledge structures as a multiagent job-shop-scheduling approach

referred to as the knowledge of a machine. This knowledge can be modeled as either a specialist or generalist structure. For example, if every machine is able to perform all specified operations, it is a generalist structure. Contrastingly, a specialist structure is given when every machine provides one operation. The assignment of tasks to a machine is similar to the assignment of tasks to a human team member and based on their specific knowledge of expertise. Moreover, the model contains a manager to schedule the jobs. From a pschological perspective the manager functions as a transactive memory which contains knowledge about the location of expertise and enhances the integration of new team members [10,18,32,29]. The manager retrieves a predefined amount of jobs J and schedules these jobs with the help of a register. This register contains all machines with their task capabilities. The machines and the manager are modeled as reactive agents and are organized hierarchically [35]. The interaction between these agent is restricted to the assignment of jobs. Each machine can provide one or multiple operations. The tasks are assigned to machines with matching capabilities. Every task t_i also includes a process duration p_i. The task assignment is summarized in the following equation:

$$\forall j \in J \; \exists t \in T \; \exists m \in M : unfinished(j) \land canProcess(m,t) \implies assign(m,t)$$

Within a shared knowledge structure team members are affected by inefficiency which derives from increased information loads, coordination overheads as well as context changes. This leads to a slower task processing [12]. In manufacturing processes a timespan for reconfiguration a machine before processing a different task is called retooling time. This retooling is defined for every task change and models the aforementioned inefficiency in human teams.

The focus of this paper is on knowledge structures in teamwork. Hence, the resilience of the team structure is a key factor in this model and needs to be tested in a dynamic environment. The primary disadvantage of specialist teams is when team members with specific knowledge become unavailable. Their irreplaceable knowledge leads to a loss of robustness. For this reason, an event system which models external effects is created. A machine is deactivated by an event until it becomes activated by an event again. In the time of deactivation, a machine cannot perform any tasks. Therefore, all jobs which are currently assigned to this machine will be reassigned by the manager. If there is no other machine with the needed qualifications, the job cannot be finished.

4 Simulating Effects of Team Cognitions

This Section describes the simulation of the job-shop-scheduling approach to team cognitions. In Section 4.1 the computational model is illustrated. Following this, the experiment setup with essential parameters and their configuration is shown in Section 4.2. The results of the simulation are illustrated in Section 4.3. Finally, Section 4.4 discusses these results as well as possible model extensions.

4.1 Computational model

The computational model is implemented in Java by using the Repast Simphony[1] framework. Fig. 3 shows the data model of the implementation.

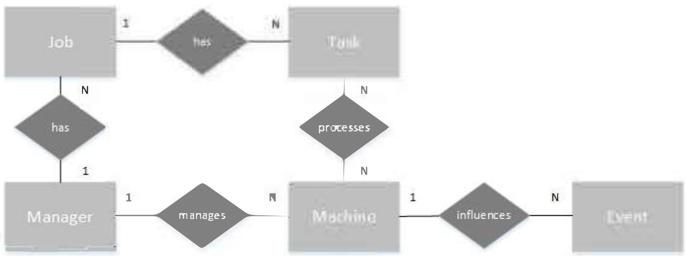

Fig. 3. Data model of the implemented multiagent-based model

The key components of this implementation are the machines and the jobs. Each job consists of a specific number of tasks, which need to be processed in the exact order. The tasks are processed by machines. Each machine receives tasks via the manager. The manager has a list of jobs and is responsible for their scheduling. The scheduling itself is a matching of the next tasks of those jobs and the capabilities of the machines. If a machine finishes a task and the job has unfinished tasks left, the job is transferred to the manager again and reassigned. The event system activates or deactivates a single machine immediately. A deactivated machine finishes its last task and sends the unfinished ones to the manager. Moreover, this machine signals the manager that it has been deactivated to avoid new task assignments. In the case of activation, the machine notifies the manager of its activation.

[1] https://repast.github.io/

4.2 Experiment setup

The simulation can be configured by a set of parameters, which are named and explained in the next paragraph. In order to ensure the comparability of simulation results a test case is defined. The specific parameter configuration which was used for the test case is described for each parameter.

– **Job quantity:** This parameter quantifies the jobs existent in the simulation, which will be created at simulation start. The test case contains *100 jobs*.
– **Task class:** The task class defines the amount of different tasks available. Each task has to be processed by minimum one machine. The different task classes a machine can handle characterize the knowledge of this machine. In the test case, *ten* different task classes were implemented and indexed.
– **Task quantity:** The task quantity defines the number of tasks a single job can contain. A job must have at least one task. In this simulation a job contains *ten* different tasks.
– **Task order:** The order in which a job has to be processed is determined by this variable. The order needs to be defined for every job. The order was chosen randomly in this test case.
– **Task duration:** The process duration of a single task is defined by its task class. In this test case, the task duration is defined by the index of the task class. A task of the first task class has the shortest process duration (*5 milliseconds*) and a task of the last task class has the longest process duration (*50 milliseconds*). The durations of the tasks in between are linearly increasing.
– **Machine quantity:** This parameter defines the amount of machines available in the simulation. The quantity is set to *ten machines*, in the test case.
– **Machine knowledge:** The knowledge of a machine is defined by their task process capabilities and needs to be set for every machine. It defines which machines can process which task classes. Moreover, the difference between a generalist and a specialist knowledge structure is of interest. The specific knowledge allocation for every machine is shown in the next Section.
– **Machine queue:** This parameter describes how many tasks a machine can store. This ensures that all machines are equally working on capacity. In this case, a machine can store *10 tasks*.
– **Retooling time:** The retooling time defines how long a machine needs to reconfigure in order to work on a task from a different class as the previous one. The retooling time was set to the arithmetic mean of the task durations.

The values for job quantity, task classes, task amount and machine quantity were chosen based on their dependencies and a manageable simulation duration. The test case configuration is defined based on their necessary complexity to show effects of different knowledge structures as presented in the next Section.

4.3 Experiment results

The simulation is configured as previously described. The machine knowledge is set to six different configurations and the simulation result is measured as the overall makespan of *100 jobs*. The knowledge configurations can be divided in specialist and generalist structures. The generalist knowledge structures are either comprehensive or partial. The partial configurations contain every task class two, three or four times. The remaining knowledge configuration contains each task class twice as well as a deactivation event for a single machine. Fig. 4 shows the results of *ten* simulated iterations.

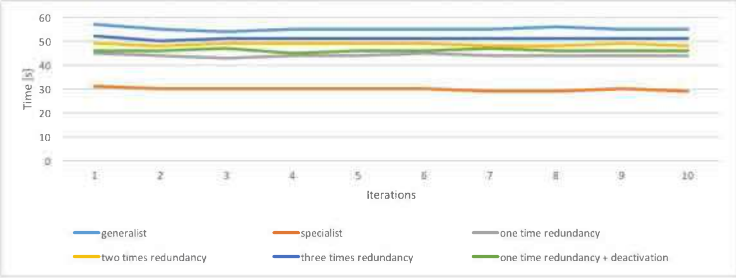

Fig. 4. Makespan as the result for simulating different knowledge structures over time

The longest makespan can be observed for the generalist knowledge structure in which every machine is able to perform every task class. The retooling time is decisive for the long duration. The shortest processing time is generated by the specialist knowledge structure because of less overhead. Raising the level of redundancy, the overall makespan is increasing, due to the fact that a higher level of redundancy enhances the probability of different task classes.The simulation with the deactivation event shows a makespan extension by *two seconds* in average.

Furthermore, there are minor variations of results, which implicates a low variance of the simulation. This shows that the knowledge structure has a much higher impact on the makespan than the randomness of the task assignment. Fig. 5 shows the average makespan and the standard deviation of the processed jobs.

Knowledge Structure	Generalist	Specialist	One time redundancy	Two times redundancy	Three times redundancy	One time redundancy + deactivation
Standard deviation	0,789 s	0,632 s	0,568 s	0,516 s	0,471 s	0,568 s
Arithmetic mean	55,2 s	29,8 s	44,1 s	48,6 s	51 s	46,1 s

Fig. 5. Standard deviation and arithmetic mean of simulation result for different knowledge structures

Compared to human team structures, the computed results are plausible. The agents process tasks slower in case of varying assignments which can be observed in human teams as well [18,41]. The results of the simulation show that divided knowledge structures are more efficient than shared ones, which coincide with psychological research [9]. Hence, the main conclusion of this simulation is the dependency of knowledge structure and makespan, which results in an optimization problem in finding a suitable team structure [27]. The model can be used to test different scenarios for knowledge configurations and simulate their effects. On the basis of these effects, assumptions about teamwork can be evaluated. These should consider the dichotomy of efficiency and resilience of different knowledge structures as well as risk assessments of possible knowledge loss. The next Section describes possible extensions which improve the model to simulate real life scenarios.

4.4 Discussion and Implications

The presented job-shop-scheduling model is a first approach toward simulating the effects of different knowledge structures in teams. The simulation results show that it is suitable for representing specialist and generalist teams and for reproducing their implications on the work performance. Nevertheless, using such a simulation as a method for managing and optimizing teamwork processes as well as for complementing classic psychological research requires several extensions of the current model. These include its application to *real-world scenarios*, a more detailed *representation of knowledge* and capabilities, *communication and adaptation* processes within a team, as well as a team's embedding in an *organizational context*.

To enhance the realism of the formal model, it is necessary to include real-life scenarios which requires the analysis of team work in practice. Moreover, psychological concepts are needed to examine and understand the effects of varying team cognitions. By conducting of field studies and laboratory experiments, the psychological insights will be gathered. This analysis focuses on qualifications an employee needs to work on specific tasks as well the level of qualification formalization. Moreover, employees learn new skills, which need to be managed and the learning process has to be structured. Summarizing, a description language to formalize a suitable team cognition model is needed which is a foundation for modeling real-life team work.

The representation of real-life scenarios requires an agent-model, which is similar to humans. The belief-desire-intention (BDI) architecture explicitly models the information, motivational and deliberative states of an agent. [30] Besides these fundamental architectural specifications, a concept of knowledge representation and knowledge processing is needed in which especially the usage, storage and forgetting of knowledge is relevant. This knowledge has to enable reasoning about a team member's environment and perceptions. In order to achieve this, a formal ontology, which is commonly used in artificial agents, should be used as a knowledge base. An ontology enables sharing more easily because of a mutual understanding. For example, a specification like OWL can be used to build such an ontology which is able to distinguish between assertional and terminological knowledge [2]. In addition, similar to humans, agents need a learning capability, which allows the acquisition of new skills.

In the previously described model, the communication between agents is limited to task assignments by the manager. However, communication between different team members is essential. In order to standardize this communication an ontology for agent communication need to be developed. Besides the communication protocol, the message flow need to be organized, e. g., by defining roles which are connected through communication channels [19,35].

In addition to architectural agent requirements, a team needs to adapt their work and communication in case of inefficiency or organizational changes. Therefore, key performance indicators need to be defined, which measure for example knowledge capacity, resilience, information efficiency or trust in the system. These measurements should lead to an improved team simulation and can be used by the agents themselves to enhance teamwork.

These model extensions should be used to model small teams and their interactions. Afterwards, the simulation of multiple teams and whole organizations. This is useful to identify complicated team configurations, where, for example, team members retire and their knowledge becomes unaccessible. Besides these economical purposes of simulating team cognitions, such simulations can be applied as a method in psychological research complement in laboratory experiments [5].

5 Conclusions

This paper has introduced a multi-agent-based approach to model knowledge in teams and to simulate the effects of varying knowledge management structures on teamwork and its performance. In order to achieve this, an interdisciplinary perspective of knowledge management has been applied, which integrates the theory of team cognitions from psychology with formalization, modeling and simulation methods from business informatics. Furthermore, the well-known job-shop-scheduling problem has been used as formalization to model knowledge structures within the spectrum of specialist and generalist teams. The simulation results show the appropriateness of job-shop-scheduling as a model to analyze different knowledge structures and to optimize team cognitions.

In the test case for the developed simulation, the specialist team processes the given tasks almost two times faster than the generalist team. Moreover, the evaluation has shown that the knowledge structure of teams is decisive for their performance. Hence, the model is a promising first step towards the vision of simulation as a method for designing and evaluating work processes in dynamic environments.

However, to achieve that goal, the classic job-shop-scheduling scenario must be extended with a more elaborate model of team cognitions, agent capacities, and adaptivity to dynamically changing environments. Such an extension has to allow for a more adequate representation of real-world teamwork processes among humans in order to facilitate the design and evaluation of knowledge management strategies. Consequently, the next step for further developments is analyze teamwork in practice and to derive capabilities, team structures, and simulation scenarios in various domains like administration, logistics, or health care. Together with a deeper integration of psychological theory, this will lead to the formulation of requirements for extending the mental model for the agents' decision-making. Thus, a further step for future work is to include approaches for practical reasoning like the Belief-Desire-Intention architecture [30] in the agent-based model, to modify them for representing team cognitions, and to validate the simulation model against results from psychological laboratory experiments and field studies. The validated agent-based simulation can then be used to analyze and optimize flexible knowledge practices in human teamwork.

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