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CHARACTERISTICS OF SIMULATION: A META-REVIEW OF MODERN SIMULATION APPLICATIONS

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ABSTRACT

Simulation studies enable practitioners and researchers to prove assumptions and hypotheses. Through experiments, they can analyze real-world and conceptual systems. Hence, simulation is an integral part of industrial and scientific work. Nevertheless, simulation applications have to adapt to modern, digitized working changes. As simulation evolves analogously to the industrial world, the scientific world must adjust accordingly, and new research streams for the next steps of simulation's evolution must be defined. This work aims at gathering and exhibiting the properties of recent simulation studies. It provides the groundwork for the definition of research streams for the future of simulation. The paper lays the foundation for prescriptive design knowledge on simulation studies through a structured literature review. Thus, researchers and practitioners are enabled to take on the current challenges of simulation based on a descriptive up-to-date data basis.

1 INTRODUCTION

Simulation studies enjoy great popularity in research and industry (Diniz et al. 2021; Moeuf et al. 2018). As simulation enables real-world and conceptual systems analysis, they often come to use for process planning, scheduling, and project management (Gutenschwager et al. 2017; Law 2015). Nevertheless, industrial applications are evolving according to the industry's new technologies. Simulation studies must adapt to these new technologies, including the internet of things, cloud computing, digital surrogates, or sovereign data ecosystem (Boschert and Rosen 2016). Prescriptive design knowledge is necessary to design simulation models that can cope with these challenges. Prescriptive design knowledge is a set of rules that specify the architecture and composition of a given artifact (Chandra et al. 2015). However, prescriptive design knowledge needs a descriptive data foundation (Möller et al. 2021a).

The research of this paper is part of a more extensive study that aims at providing prescriptive design principles and development rules for modern simulation applications. The starting point for this research project is the paradigm of design science, according to Hevner et al. (2004). The question of how something must be designed describes an essential foundation in the context of design science and is also becoming increasingly important in the context of business information systems for the creation of IT artifacts (Carlsson et al. 2011; Hevner et al. 2004). Primary artifacts in the context of design science are models, methods, constructs, and instantiations (March and Smith 1995). Hence, we aim to derive descriptional models of recent simulation application studies. A model's description of a specific repetitive pattern of an IT artifact provides an archetype (van der Valk et al. 2021). As a foundation for these archetypes, we need

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a thorough empirical and structurally analyzed data basis (Möller et al. 2021b). Hence, the overall research objective of this paper is to derive this data basis through a structured literature analysis that can then be used for future archetype design. Thus, the paper must be seen as part of a more extensive research endeavor. Alongside the research objective are the research questions (RQs):

RQ1: How does a recently conducted simulation application study look like?

With this RQ, we want to gain a description of the properties that recently conducted simulation application studies possess. The properties are the most relevant distinguishing characteristics for archetypical patterns. The patterns contain a specific configuration of the properties. Hence, we need a global view of all properties.

RQ2: What are the resulting research streams for future research on the simulation?

The RQs provide a framework for the analysis of the data basis. We seek to understand the structure of recently conducted simulation application studies.

For the remainder of the paper, we start with simulation basics and their application studies. We outline our research approach in Section 3 and provide the observations in Section 4. Section 5 discusses remarkable results and outlines future research streams.

2 BASICS OF SIMULATION

According to Law (2015), already existing or not yet existing complex systems are analyzed and studied with the two techniques of modeling and simulation. Following the definition of Schmidt and Taylor (1970), a system is described as a collection of interrelated objects that can interact with each other. The simplified representation of such a real-world system is called a model by Banks (2013). Simulation can be used when the capabilities of an analytical model are no longer sufficient, for example, because it is too complicated or takes too long to find a solution. Definitions of simulation vary in the literature. While Shannon (1998) defines simulation as the model design process of a real system and conducting experiments with this model to understand the system's behavior, Banks (2013) understands it as an imitation of a real-world process focusing on its operations and the progress over time. Law (2015) describes simulation as an imitation of the functions of various kinds of real-world processes and facilities. We base the paper on the Verein Deutscher Ingenieure (2014, p. 28) definition of simulation: Simulation is a "representation of a system with its dynamic processes in an experimental model to reach findings, which are transferable to reality; in particular, the processes are developed over time".

Looking at all the definitions, it can be noted that the essential element of the simulation is the model. Law (2015) describes such a simulation model in three dimensions:

- Deterministic and stochastic. The difference between deterministic and stochastic simulation models is the inclusion of probabilistic properties. Stochastic simulation models consider probabilities and, thus, randomness. Deterministic simulation models do not assume any probabilistic properties.
- Static and dynamic. While static simulation models represent the system at a particular point in time or independently of the time advance, dynamic simulation models consider the system's evolution over time.
- Continuous and discrete (concerning time). In continuous simulation models, the state of the model changes continuously. In time-discrete simulation models, the state changes only at specific, separated points in time. Here, classifying the system's variables into continuous and discrete should also be considered (Gutenschwager et al. 2017).

The distinction of the time horizon of the simulated systems into finite or infinite complements the previously listed dimensions. The implementation of simulation studies requires a targeted approach, which is usually implemented with the help of process models. There are established procedural models in the literature, e.g., the model presented by Banks (2013) or the model proposed by Rabe et al. (2008). The second model is widely used in German-speaking countries. Essential components of any simulation study are credibility and validity, especially of the simulation model, during all phases (Law 2008). The literature provides a variety of techniques used to achieve verification and validation (V&V) of a simulation model. Examples of this are the process models of Sargent (2010) or Rabe et al. (2008) (short English version in Rabe et al. 2009). Rabe et al. (2008) have described the structured process of conducting V&V within the simulation study and listed several suitable techniques. They have categorized these techniques and discussed additional aspects, such as the subjectivity of the methods.

3 RESEARCH DESIGN

The overall objective of the overarching research study is the identification of archetypes. Archetypes, or archetypical patterns, are typical examples of a specific object or system (Oxford Dictionary 2020). They describe a combination of certain properties of the analyzed subject. Each combination is characteristic for the given configuration. An archetype provides a design solution for the subject in connection with surrounding influences and requirements. Originally steaming from biological contexts, archetypes enjoy increasing interest in information system research because they enable the researcher to identify clusters and provide a clear picture of the instance's configuration of the portrayed objects (cf. Weking et al. 2018; Beinke et al. 2018).

As Möller et al. (2021b) showed in their analysis of taxonomies in IS research, archetypes are often preceded by taxonomies, or at least by morphological concept matrixes, at which we aim in this paper. We start with a structured literature review in adherence to the guidelines from Webster and Watson (2002) and vom Brocke et al. (2009). First, we determined the research objective (see Section 1) and defined the search strings (Figure 1). Then, we searched in the proceedings of the Winter Simulation Conferences for the terms "application", "practic", "use case", and "implement". We focus on the papers published within the time frame 2016 to 2020 to get an accurate point of view on recent papers. At the point of our research, more recent papers from 2021 were not accessible. Furthermore, we limit the search to the WSC proceedings, as we deem the conference the leading one for simulation at which all novel work on simulation can be found.

This search yielded 219 publications. The first elimination of short papers brought us 182 documents from these WSCs for consideration. In the next step, we applied the quality criteria to the data basis and eliminated 58 papers that were irrelevant or had no thorough argumentation. We analyzed 20 randomly selected papers to gain a first draft of a morphological concept matrix. For this purpose, we brainstormed the properties we expect from a simulation application. Following Section 2, we commenced with eight dimensions (Table 1).

After the first iteration with 20 papers, we discussed the results in the author group, refined the eight dimensions with the first characteristics, and added two dimensions (Table 1). Then, we analyzed the remaining 104 documents in a second iteration, through which we gained theoretical saturation. We present the results in the next section. Finally, 124 papers and ten dimensions with several characteristics could be considered and derived.

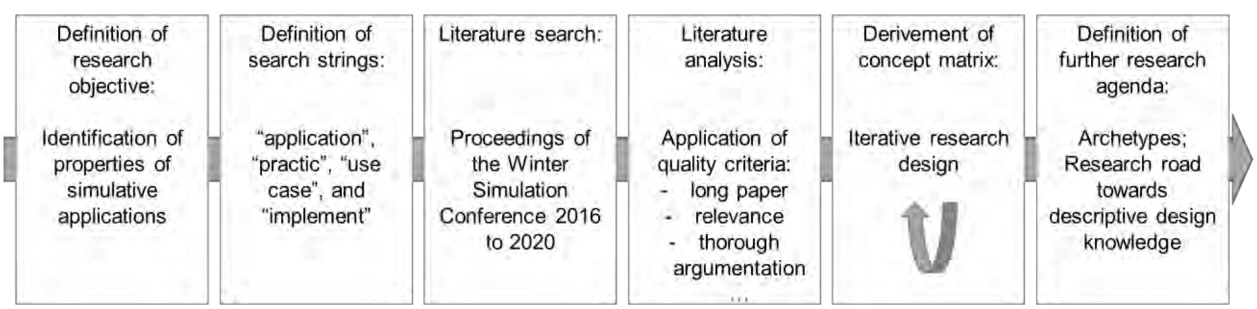

Figure 1: Research design according to Vom Brocke et al. (2009) and Webster and Watson (2002).

Albeit we did our search with a certain type of simulation in mind that corresponds to the definition given in Section 2, it was not necessary to limit the results to this definition as the analyzed works solely revolved around the type of simulation according to Section 2. New simulation techniques, such as virtual/artificial realities or 3D simulations, are included through the different characteristics we describe in the next section.

4 RECENT SIMULATION APPLICATIONS – THE LITERATURE ANALYSIS

The sampling of the literature yields fascinating insights into the simulation studies of the past years. In total, we analyzed 124 publications. The simulation studies are uniformly distributed from 2016 to 2020, as shown in Figure 2. Peaks are noticeable in 2017 and 2019, but application studies are essential every year.

To classify the literature base, we apply the research design described above. Table 1 provides a detailed description of the dimensions.

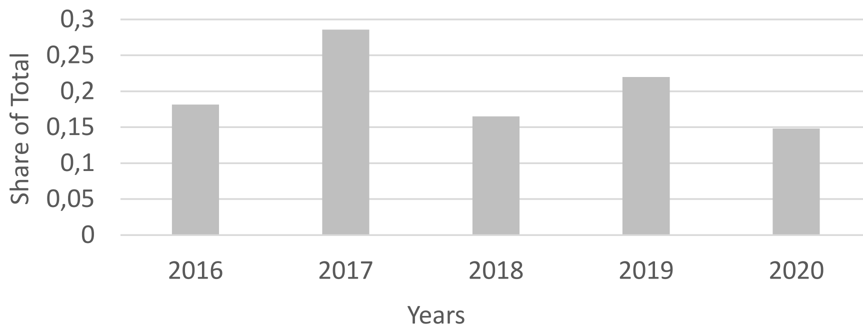

Figure 2: Yearly distribution of simulation application studies.

4.1 Dimensions of Recent Simulation Application Studies

This section outlines the dimensions of the first iteration, in which we analyzed 20 simulation application studies. The dimensions are the study's V&V, the model type, the experiment plan, the downstream services, the data management, the simulation tool, the domain, and the data input.

Table 1: Dimensions during the literature search.

Dimensions Before 1st Iteration	Dimensions After 1st & 2nd Iteration	Description
V&V	V&V	What are the conducted evaluation processes?
Model Type	Model Type	What kind of a model are we looking at?
Experiment Plan	Experiment Plan	Is there an experimental plan provided?
Downstream Services	Downstream Services	What are additional services achieved with the simulation application?
Data Management	Data Management	What does data management look like?
Tool	Tool	What tools were used?
Domain	Domain	Which domain is addressed?
Data Input	Data Input	What does the data input look like?
	Simulation Method	Which method was used?
	Process Model	What kind of process model was used?

Verification & Validation: The first dimension refers to the V&V of the simulation study. V&V is a crucial part of every simulation study, and several authors prescribe the conduction of V&V, e.g., Rabe et al. (2008), Verein Deutscher Ingenieure (2014), or Benington (1983). Many mechanisms are available that are usable for the V&V of a simulation study. Rabe et al. (2008) suggest using different V&V techniques dependent on the specific step within a simulation study. As techniques, they propose, for example, desk checks, extreme condition tests, or structured walkthroughs (Rabe et al. 2008).

Model Type: The next dimension is the model type. In this dimension, we search for the specific construction of the model. The model type depends on the simulation study's purpose. Hence, many different model types are thinkable (Fishwick 1998). Gutenschwager et al. (2017) suggest the classification of the model types in dependence on the time behavior (static/dynamic), the quantity of time and the system states (discrete/continuous), the randomness (stochastic/deterministic), and whether the system is terminating.

Experiment Plan: Simulation studies require planned experiments (Verein Deutscher Ingenieure 2014). It defines the altered parameters and systemizes the order of the simulation runs to gain the most efficient approach. For evaluating the experiments, a precise plan is mandatory (Verein Deutscher Ingenieure 2014). Amongst others, Barton (2013) recommends a five-step approach: define the goals, identify and classify the variables, construct a probability model, choose a proven experiment design, and validate the design, as an example.

Downstream Services: Simulation studies are not stand-alone works. They are part of greater projects with an overlaying objective (Law 2015). Hence, simulation studies are followed by several further steps of data processing. We label this work with the data as services. This dimension shall provide information about services that track the simulation study downstream. We expect the classical services, i.e., analysis and optimization, but we also expect novel and interesting insights.

Data Management: This dimension contains ways for handling the simulation data. Data management is crucial to the success of a simulation study (Skoogh and Johansson 2008). For data management, several solutions are usable. Besides classic approaches, e.g., databases, other technologies come into action. Virtual constructs like digital surrogates or (cloud) platforms for data handling and long-term data storage are practical to use. As data management possibilities are manifold, we expect a variety of different aspects of data management technologies.

Simulation Tool: The environment in which the simulation runs is the simulation tool. There are a plethora of tools for simulation. In accordance with the different types of simulation, i.e., discrete/continuous or static/dynamic, there are specialized tools for individual simulation technologies. Overviews of various simulation tools are frequently published, i.e., Klingstam and Gullander (1999), Gupta et al. (2013), or Schönberger (2012).

Domain: The concrete domains of the application studies are highly diverse, as is the landscape of simulation application studies (Law 2015). In this dimension, we expect the sectors of logistics and production as focus points, as well as healthcare. However, at this point, we do not limit the analysis to a specific domain.

Data Input: This dimension illuminates the sources of the input data. The input data are highly relevant to the quality of the simulation study, and some research was done on the quality of input data (Bokrantz et al. 2018; Skoogh and Johansson 2008). Historically, the simulation gets its data from CAx, ERP, or production planning systems (Gutenschwager et al. 2017).

Simulation Method: The simulation method was added during the first iteration. In accordance with Section 2, we expect different methods for the core simulation. Thinkable are discrete or continuous simulation, agent-based models, Monte Carlo approaches, or hybrid simulation that combines several methods.

Process Model: The process model illustrates the structured procedure during the simulation study. Over the last years, a plethora of process models has been developed. Notables are the models of Law (2015), Banks (2013), Robinson (2004), or Verein Deutscher Ingenieure (2014). All have in common that they enhance the actual simulation with initial and successive processes. We added this dimension during the first iteration. As many simulation studies do not follow one of the published process models, we accept any structured approach for the study as a process model.

The second iteration showed the so-called theoretical saturation (Webster and Watson 2002), as no additional dimension is needed for the analyzed objects' thorough description. We offer the collected properties of each dimension in the next section.

4.2 Observations and Conceptual Matrix

The dimensions from the literature analysis conclude in the conceptual matrix.

Table 2: Conceptual matrix of recent simulation studies.

Dimensions	Properties						
V&V	Test And Comparison (30%)	Case Study (7%)	Multiple Techniques (6%)	Not Further Specified (6%)	Other Techniques (12%)	No Technique Provided (39%)	
Model Type	Mathematical/ Algorithmic Model (44%)	Block-(Tool)-Based (7%)	3D-Model (5%)	Multimodel (4%)	Other (5%)	Not Specified (35%)	
Experiment Plan	No Experiment Plan Provided (26%)	Detailed Case Description (16%)	Flow Chart (10%)	Not Further Specified (48%)			
Downstream Services	Analysis (56%)	Optimization (35%)	Prediction (10%)	Evaluation (10%)	Decision Support (3%)	Employee-Training (1%)	Multiple Services (17%)
Data Management	None Provided (83%)	Database (8%)	Excel (5%)	Multiple Entities (2%)	Not Further Specified (2%)		
Simulation Tool	AnyLogic (15%)	MATLAB (6%)	Arena (6%)	Not Named (19%)	Rest (54%) (See Fig. 3)		
Domain	Logistics (24%)	Production (21%)	Healthcare (18%)	Public Services (15%)	Other (22%)		
Data Input	Real-World Data (47%)	Multiple Inputs (14%)	Empirical Study (6%)	Historical Data (6%)	Experimental Data (4%)	None Provided (23%)	
Simulation Method	Discrete Event Simulation DES (44%)	Hybrid (DES / ABM) (14%)	Monte Carlo (9%)	Agent-Based Model ABM (7%)	Hybrid (6%)	None Provided (20%)	
Process Model	None Provided (72%)	Used But Not Specified (21%)	Used And Specified (7%)				

Verification & Validation: Within this research study, 50 % of the simulation studies (in the following called the objects) analyzed in iteration one do not mention the application of any V&V technique. 12.5 % describe using a not further specified V&V technique, and 37.5 % mention a specific technique, e.g., expert consultations or goodness of fit tests. In iteration two, this trend continues. The vast majority of the objects do not mention any kind of V&V at all (39 %). Half of the remaining objects use some type of comparison as the V&V technique. Seven percent of the overall objects use case studies for V&V, and six percent combine various methods for their evaluation. Equally, six percent of the objects consult experts for the V&V or state that they conducted a V&V but do not specify the technique. The remaining shares split themselves between various V&V methods, like the Turing or performance tests.

Model Type: During our analysis, we identified three significant model type groups. The largest group is the mathematical or algorithmic models, with a share of 44 %. These models make up for most simulation studies overall. The block or tool-based models are the second-largest, noteworthy group (7 %). Here, the simulation model is created per drag and drop or through clicks in the simulation tool's modeling interface. Five percent of the objects use 3D models primarily designed with CAx programs, and four percent use and combine several different modeling types. Hence, these may be deemed irrelevant for a broad application as of today.

Experiment Plan: In the first iteration, 62.5 % of the objects do not mention any planned or structured approach for simulation experiments. The remaining 37.5 % mention a structured experiment approach but do not specify the experiment plan in detail. Unfortunately, we see this trend continuing in the second iteration. 74 % of the objects only indicate that an experiment plan exists (48 %) or do not use any experiment plan for the simulation study whatsoever (26 %). Ten percent use flow charts as experiment design and 16 % provide a detailed description of the conducted experiments.

Downstream Services: Each object is part of a greater context, and hence, the simulation studies are followed by downstream services. Namely, these services are analysis (56 %), optimization (35 %), prediction (10 %), evaluation (10 %), decision support (3 %), and employee-training (1 %). 17 % of the objects provide more than one downstream service, of which the vast majority combine another service with optimization. Notable is the inclusion of downstream services in every simulation study deemed relevant. This shows that a simulation study is not a stand-alone solution but only enfolds its true potential in combination with further data processing steps.

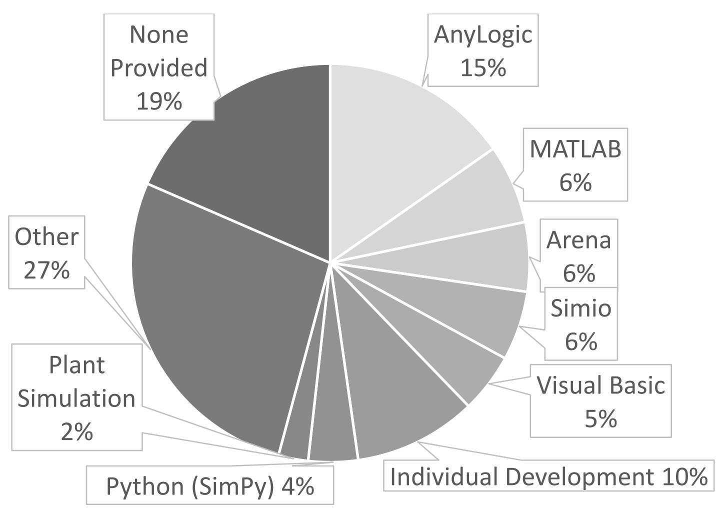

Figure 3: Used simulation tools.

Data Management: Most analyzed studies do not describe any kind of data management. 83 % of the simulation studies do not provide a related strategy. The remaining 17 % describe their data management strategies. Significant shares use a database and its content management tools for data management. A wide array of solutions can be found within the databases due to the individual restraints concerning data management. Another significant share (5 %) uses Excel or similar spreadsheet tools for data management. This is convenient, as many tools provide the option of data transfer via CSV or even a direct interface to Excel. Four percent use multiple instruments or do not specify the device for data management.

Simulation Tool: We expect various simulation tools with a growing number of objects. We could identify several tools in the relatively small first iteration, e.g., MATLAB, AnyLogic, or Imprint. Many objects name the used tool, as only 19 % of the overall objects do not name the used simulation tool. Furthermore, interesting numbers are extractable. We identify AnyLogic as the most used tool with a share of 15 %. Three other tools share the second place with six percent each – MATLAB, Arena, and Simio. Five percent of the objects use Visual-Basic-based simulations, and ten percent develop an individual solution for the simulation study, of which at least 6 % are based on JAVA. The remainder (33 %) use a tool of less importance (see Figure 3).

Domain: In iteration one, no primary application domain could be identified due to the small number of analyzed objects. The domains so far are, namely, public services, energy management, mining processes, queuing processes, gaming, and healthcare. Iteration two provides a sufficient database for the building of patterns. The largest share of simulation studies is focused on logistics and supply chain management (24 %). Closely following is the production systems sector, as 21 % of the objects deal with production systems. Under this umbrella, many different subsectors are subsumed, as production, for example, includes automotive or semiconductors. Other essential domains are healthcare applications (18 %) and public services (15 %), which also contain infrastructural applications in smart city contexts. The remaining 22 % of the application studies address other domains, e.g., energy management or disaster prediction. Nevertheless, a meaningful difference between simulations applied in industry, service sector, or governmental institutions is not visible.

Data Input: 37.5 % of the first iteration's objects do not describe the data source. 25 % each gain their data from empirical studies or historical data. 12.5 % use experimental data that are created for the simulation study. In the second iteration, the distributions change. Nearly half of the studies (47 %) gain their data from real-world operations as (near) real-time updates. This is a novum as classical simulation studies merely used historical or empirical data (van der Valk et al. 2020). In connection with the steep rise in up-to-date real-world data usage, historical datasets and empirical studies just provided the data input for twelve percent of the simulation studies. Another critical data source is the combination of different data inputs (14 %). These multiple inputs often include combined real-world, historical, and empirical data. 23 % of the simulation studies do not provide any information about their data sources.

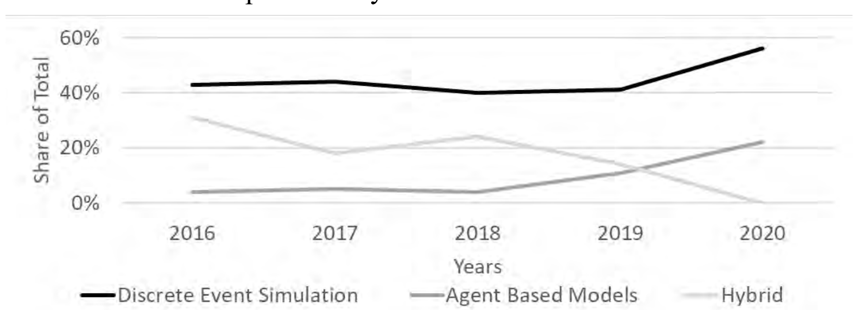

Figure 4: Yearly distribution of the simulation methods.

Simulation Method: The simulation studies use different simulation methods. Most common is still the usage of discrete event simulation (44 %). All other simulation methods are of less importance. In the second place, simulation methods that combinate discrete event simulation with agent-based models follow with 14 %. Monte Carlo simulation and actual agent-based modeling have a share of nine, respectively, seven percent. Further hybrid simulation methods that contain individual combinations make up six percent. 20 % of the objects do not specify their simulation method or use another alternative, e.g., continuous approaches. A closer look at the yearly distribution provides further exciting insights (Figure 4).

The discrete event simulation ranges in the first place in each year. Nevertheless, the agent-based method grew over the years and proceeds from last place in 2016 to second place in 2020. At the same time, the hybrid approaches lose importance during this period.

Process Model: Although the necessity of a process model is common knowledge within the simulation community, a significant share of the simulation studies do not use a process model of any kind for their work. 72 % of the objects do not describe their process model, and hence, we have to assume that no such model is used. On the contrary, 28 % of the objects use a process model, of which seven percent specify the process model in more detail. The process models provided by Law (2015) and the Verein Deutscher Ingenieure (2014) are commonly used.

5 SUMMARY AND FUTURE RESEARCH

The review yields very interesting insights into recent simulation studies. As per RQ1 (How does a recently conducted simulation application study look like?), a recently conducted simulation study addresses a problem in logistics, production, or healthcare and tackles the issue with a discrete event simulation. The study uses a database for data management and utilizes mathematical and algorithmic modeling approaches. For the experiments, a structured approach is used. Probably, a detailed case is used for that. The simulation includes analysis and optimization processes as downstream services. The simulation model relies on updated information from the system with frequent updates. As V&V technique, tests and comparisons are used. However, this only describes the pattern with the most-used properties. The use cases for simulation are highly individual, and so are the configurations of a specific simulation study.

Furthermore, there are some discrepancies between our expectations and the results. Coming from these expectations, we have defined future research streams for developing prescriptive design knowledge about "modern" simulation studies. The first big gap between expectation and results is the considerable share of simulation studies that do not evaluate their results. A V&V is a crucial part of a simulation study. Nevertheless, the V&V is often not part of such a study. Hence, prescriptive design knowledge on the integration of V&V into simulation studies should be revised (Figure 5). The following path is a new detailing of experiment plans. A thorough experiment plan will help to gain more structured results from the simulation studies. A standardized approach to the structure of the experiment plans will help practitioners while conducting the simulation study. Thirdly, programs for data management should be designed and enforced to ensure a reference framework for handling the simulation data (input, onsite, and output).

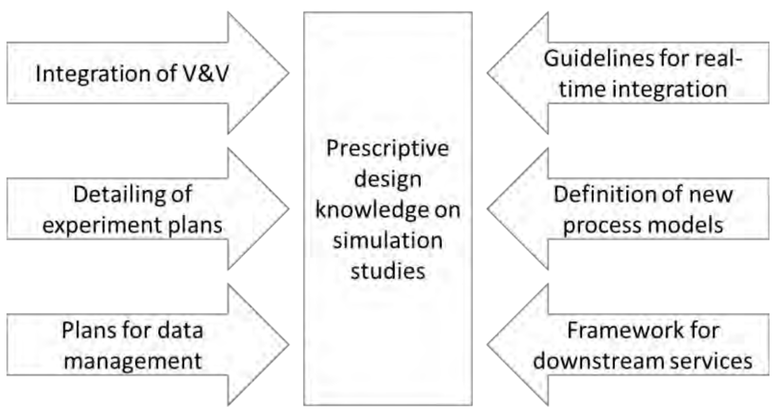

Figure 5. Possible paths for future research.

As many simulation studies already use real-time data, we need more research work on guidelines for their integration. This primarily includes ensuring data quality and safety of the acquired data. This calls for a revision of the already existing process models. A revised model that addresses the challenges of more recent simulation applications is of better usability for the practitioners. Lastly, simulation studies already include downstream services. With the advancement of service-oriented ecosystems, a framework for combining simulation and downstream services is necessary.

This paper reviews recent simulation studies conducted since 2016. We conducted a structured literature review on a sound literature base and concluded these simulation studies' properties in a conceptual matrix. Combining the different properties create a thorough picture of today's simulation studies. Furthermore, it paves the way for future research on simulation to cope with recent advances in information systems research. Intending to gain prescriptive design knowledge, the literature review forms a profound research base. Besides artifacts, like archetypes, reference models, and design principles, the research should focus on V&V, experiment plans, or the inclusion of service-oriented systems.

Our work is subject to certain limitations. As the review scope for the literature analysis is subjective, other research teams might define different scopes and, therefore, might find other results. Secondly, in a similar way to coding, this process is prone to subjective influences. We limit our research to the concepts of the simulation applications and, therefore, neglect the deeper review of the application itself. Nevertheless, the deep-dive on application will be part of future research.

This research provides several contributions. As scientific contributions, this paper analyzes recent simulation studies and provides comprehensive insights into the state of the art of simulation. This lays the foundation for further research. Building upon this foundation, future research can derive prescriptive design knowledge and thus, will provide interesting insights into modern simulation applications. Furthermore, the work provides practitioners with an overview of how recent simulation studies are designed. This provides input for their planned simulation studies. At the very least, practitioners will gain insights into the fast-evolving field of simulation research.

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