(Re)-discovering Simulation as a Critical Element of OM/SCM Research: Call for Research

Structured Abstract

Purpose: Focuses on (re-)introducing computer simulation as a part of the research paradigm. Simulation is a widely applied research method in supply chain and operations management. However, leading journals, such as the *International Journal of Operations and Production Management,* have often been reluctant to accept simulation studies. Provides guidelines on how to conduct simulation research that advances theory, is relevant, and matters.

Design/methodology/approach: This study pooled the viewpoints of the editorial team of the *International Journal of Operations and Production Management* and authors of simulation studies. We debated our views and outlined why simulation is important and what a compelling simulation should look like.

Findings: There is an increasing importance of considering uncertainty, an increasing interest in dynamic phenomena, such as the transient response(s) to disruptions, and an increasing need to consider complementary outcomes, such as sustainability, which many researchers believe can be tackled by big data and modern analytical tools. Building, elaborating, and testing theory by purposeful experimentation is the strength of computer simulation. We therefore argue that simulation should play an important role in supply chain and operations management research, but for this it also has to evolve away from simply generating and analyzing data. Four types of simulation research with much promise are outlined: empirical grounded simulation, simulation that establish causality, simulation that supplements machine learning, artificial intelligence and analytics, and simulation for sensitive environments.

Originality: Identifies reasons why simulation is important for understanding and responding to today's business and societal challenges. Provides some guidance on how to design good simulation studies in this context. Links simulation to empirical research and theory going beyond multi-method studies.

Keywords: Simulation, Uncertainty, Causality, Big Data, Theory Building, Research Paradigm.

Paper Type: Viewpoint

1. Introduction

Plus ça change; plus c'est la même chose! (Jean-Baptiste Alphonse Karr)
(The more things change; the more they stay the same!)

The last years have seen the theory and practice of supply chain and operations management undergo major changes. These changes have in part reflected the emergence of new challenges that both practitioners and researchers in these areas have to face. For example, the price-driven, strategically decoupled supply chain – a supply chain strongly built around lean principles and practices – is challenged by the COVID-19 pandemic and systemic disruptions, which led to a transition to supply chain approaches that emphasize new strategic dimensions of performance, such as responsiveness, resilience or plasticity. We have also seen the emergence of more demands for complementary outcomes such as sustainability, innovation, and security (Van Wassenhove, 2019), while uncertainty has replaced risk as a major trait of the problems now being encountered (Browning *et al*., 2023). We have also encountered new tribulations such as disruptions to the supply chain due to ransomware attacks, cybersecurity breaches, and the complete breakdown of supply chains. We have seen suppliers gain increased power because of these problems.

On the positive side, new methodological capabilities and resources emerged. Researchers now have access to big data, along with its associated problems and challenges. We also have seen advances in analytical techniques – developments drawn from either econometrics or machine learning or artificial intelligence. The combination of these new challenges and the emergence of new sources of data and analytical procedures has led some researchers to believe that the solution to these challenges must lie in these new sources of data and techniques. However, as indicated by the quote included at the beginning of this paper, it is our position that, while many of the problems, contexts, data sources, and methodological tools have changed, the fundamental issues when designing solutions for managing supply chains and operations remain constant. These issues include concerns of securing, accessing, and cleaning data, and retrodicting (explaining past events), predicting (new events or states), and understanding/explaining, i.e., answering the "why" and "how" questions by uncovering causal structures, relationships and their boundary conditions (Wacker, 1998).

While it is possible to get overwhelmed or intimidated by these new problems, data sources, and analytical techniques, it is sometimes useful to take a step back and to take stock of the tools and procedures available to the modern researcher. Part of this process should include identifying and becoming reacquainted with past tools which are still relevant and of discarding those procedures that are no longer appropriate (for whatever reason). In taking stock, it is important to not only reevaluate the tools but also to re-assess the extent to which these tools, old and new, are complements or substitutes. Assessing the usefulness of simulation is the major objective of this paper. Specifically, this paper explores the following issues:

- What are the major challenges and issues facing supply chain and operations management researchers in today's environment?
- To what extent are the 'modern' tools (e.g., machine learning, artificial intelligence) sufficient in addressing these research needs?
- What is simulation and why should it be considered seriously as part of the researcher's tool kit?

Our goal is not simply to re-introduce simulation but rather to position it in a research framework that enables researchers to better understand how the various research tools fit together. We view simulation as a very useful and important complement to the recent developments. It is our position that research demands that the researcher addresses a wide variety of problems and questions. No tool, no matter how powerful, can effectively address all of these demands; rather tools must be used where and when they make the most sense and adapted to the specific research problems. Simulation is one such tool.

2. Emerging Research Challenges

As previously noted, the last years have seen some major challenges emerge in the supply chain and operations management fields. While these challenges are not new, they gain in prominence compared to, for example, variability, which has been a focus of supply chain and operations management at least since the introduction of scientific management in the 19th century. Synthesizing the existing research that has taken place, combined with a review of actual events leads to themes such as the following.

2.1 Increasing importance of uncertainty

Risk, as noted by the extensive research into risk management in the supply chain (Sodhi et al., 2012), has played a major role in past research. Using the Knightian framework (Knight, 1921) of uncertainty and risk, risk involves situations where the researcher is faced by two distributions – the probability of an event taking place and the probability of its impact – which the researcher could quantify. In contrast, uncertainty refers to a lack of any quantifiable knowledge about either one or both of these distributions, resulting in challenges (such as unanticipated effects) arising from "unknown unknowns" and struggles about how to methodologically grasp such situations (Matos *et al.*, 2020).

A good example of uncertainty involves the ship Evergreen (Petras *et al*., 2021), which became stuck on March 23, 2021, when it lodged itself diagonally in the Suez Canal. The resulting blockage prevented ships from using the Suez Canal, with the result that at one point there were more than 360 ships blocked from using the canal. The resulting traffic jam severely impacted supply chains, preventing an estimated $9.6 billion USD worth of trade (Harper, 2021). By any measure, this event can be viewed as an example of uncertainty in action. Still, it can be classified as a grey swan (Akkermans, & Van Wassenhove, 2013), which highlights the shear impossibility of predicting unknown unknowns.

There is an adage for uncertainty – you cannot predict it, but you must prepare for it. This means that researcher, managers, and policy-makers have become concerned with scenario planning (e.g. Dani *et al*., 2008; Desai, 2012; Johnston *et al*., 2008; Joglekar *et al*., 2021; Phadnis & Jogklekar, 2021; Lapide, 2022) and "what-if" analysis to evaluate potential impacts and means to buffer or prevent them. In this context, simulation plays an important role (Saisridhar *et al*., 2023).

2.2 Increasing interest in the transient response(s)

In the last years, supply chains have experienced widespread disruptions, for example, the Evergreen (previously discussed). Other examples include the chip shortage and its impact on the production of cars or the war in the Ukraine and its impact on battery and car production. Whenever a system is shocked, it experiences a period during which the system is no longer in steady state. During this non-steady-state period, the system is involved in a transient response. Figure 1 provides an example of such a transient response.

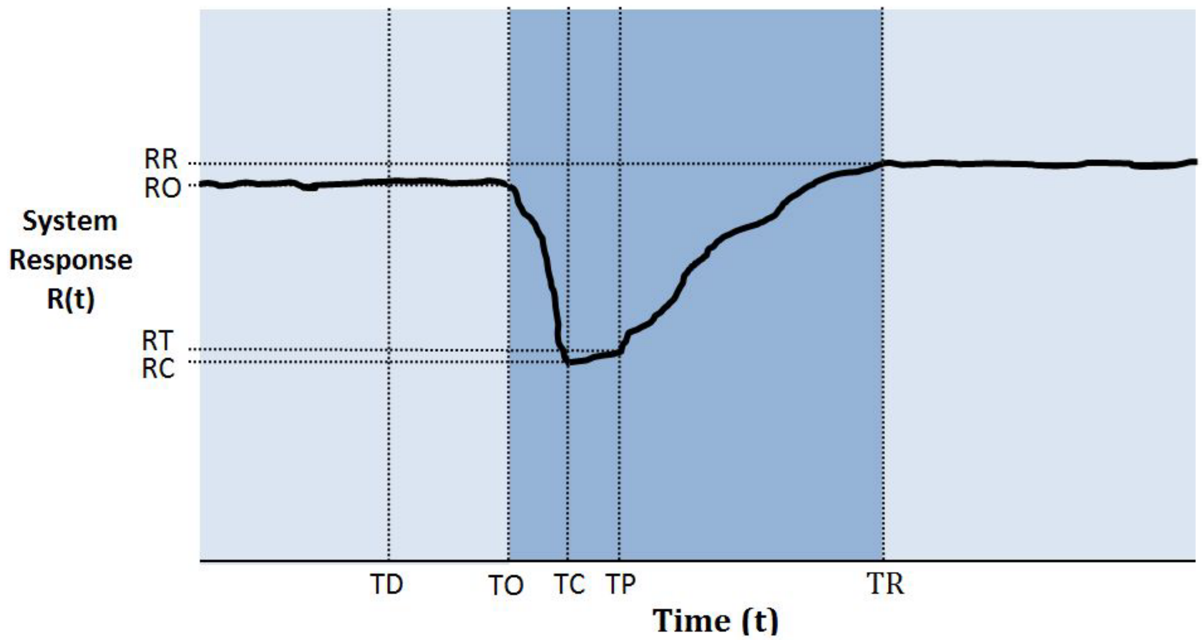

Figure 1: The Transient Response – An Example (from Melnyk et al., 2014, p. 618)

This diagram identifies many of the dimensions critical to the study of how a system responds over time to a disruption. Prior to the disruption, the system is operating at an output level of RO. The disruption takes place at time TD but its impact on the organization is felt at TO. The parameters describe how the organization's performance responds over time until a new steady-state is reached at TR, with the new post-disruption steady-state being described by RR. Wieland & Durach (2021) recently redefined resilience as the capacity of a system to persist, adapt, or transform in the face of change. If this new state RR is equivalent to RO, then we talk about engineering resilience and the system persists, if RR is different from RO then we talk about social-ecological resilience and the system adapts or transforms. In practice, a system likely persists, adapts and transforms according to business need.

As can be seen from Figure 1, critical to the study of disruptions is the identification of those factors that influence the transient response, understanding how these factors influence the characteristics of the transient response, and identifying what can be done to minimize the adverse impacts observed over the transient response. These transient responses involve both time and quantity. While quantitative methods are powerful in quantifying effects and determining optimal system parameters, they cannot appropriately capture time. Simulation provides a unique 'simulation time', which makes it specifically useful to assess transient responses.

Improvements of operations and supply chains on a social and ecological scale are often driven by shock events that disrupt the status-quo – be it a catastrophe or a powerful civil society campaign. Shocks such as the Rana Plaza garment factory collapse (Huq et al., 2016) or cases of modern slavery on tomato farms around Immokalee, South Florida (Kunz et al., 2023) may open the opportunity to find a new steady state of enhanced working conditions as well as health and safety standards (Gold et al., 2020; Kunz et al., 2023). More generally, simulation can shed light on systemic responses after the shock has caused a normative crisis regarding the legitimacy of the social and environmental impacts of supply chains (Kunz et al., 2023). Simulation helps analyzing time-dependent responses of key actors – including time delays and feed-back loops – and the effectiveness of their strategies within the context of complex cultural, political and legal structures along multiple stages of supply chains that might also be destabilized. It is therefore a key methodological tool for analyzing sustainability transformations since it can model dynamic interaction of multiple players.

2.3 Making sense of big data

The last years have seen the emergence of big data as a driving issue within supply chain and operations management research. One of the challenges offered by such data is the need to identify and describe underlying patterns hidden in this data. As noted by Shiffrin (2016), this is an area in which techniques such as machine learning, artificial learning, and analytics excel. However, it should be noted that these tools excel at historic patterns and they do not create a model but rather treat the system under study as a black box. The former questions their usefulness for low probability, high impact events that have been a cause of recent disruptions. The latter leads to the problems of explainable artificial intelligence, legitimization of decisions based on artificial intelligence and ethical failures. Most researchers agree that human judgment and analytics have unique, opposite strengths and weaknesses, which is called "Moravec's Paradox" (Browning *et al*., 2023), and that the integration of both is the key to reaping the full benefits of big data and analytics. Simulation provides a means to combine human judgment with analytics through its modelling capabilities.

2.4 Uncovering hidden causality

Observation and analysis are often sufficient for prediction, but managers do not just want to predict disruptions or that something goes wrong. They want to take action. To predict the effect of actions, in addition a causal structure is required (Pearl, 2009). Causality, as described by Hunt (1991) and Pearl *et al*. (2016), is important because it uncovers and explains relationships. It identifies the independent variables, the dependent variables, and the nature of the relationship between the independent and dependent variables, as well as the factors influencing these relationships (Wacker, 1998). It also establishes the scope of the relationships. Causality, as will be subsequently pointed out, imposes some demanding requirements on researchers – requirements that cannot be satisfied by simple correlation studies. These are requirements of temporality, exclusivity, and precedence. Most importantly, there is a need for experiments and thus replication. In empirical research this is realized by subdividing the sample, since real time events just occur once. This introduces sampling biases about which a lot has been written. Moreover, there are always problems of endogeneity and common causes since the environment can never be fully controlled. Simulation provides a controlled environment in which (simulation) time can be replicated and experiments can be repeated purposefully. Using common random number streams, the same sample can be subject to different treatments in the same (simulation) time.

3. Assessing Modern Analytical Tools

There is little doubt that the potential of big data, machine learning, artificial intelligence, and analytics is significant for research and practice but it still remains to be fully realized (e.g., Ma *et al*., 2020; Choubey *et al*., 2021; Mullins, 2021; Mustak *et al*., 2021; Cadden *et al*., 2022). The challenges offered by big data (that of its sheer size) can only be effectively addressed by drawing on the capabilities of these tools and approaches (Shiffrin, 2016). However, it is also important to recognize that currently (as of the writing of the article) what these tools excel at is finding and fitting patterns within historic data. This means that these capabilities are primarily backwards oriented, they may have difficulty in dealing with transient response, and they may be challenged by uncertainty (where the past may no longer be indicative of the future). Since big data and its associated tools are limited to what has been done (rather than by what could happen), these tools may also not be highly appropriate for carrying out "what if" analysis. While these techniques may excel at identifying patterns and correlations (where correlations can be regarded as a form of pattern), they therefore currently may not be reliably tasked with uncovering causality. These difficulties were best summarized by Shiffrin (2016: 7308):

> "However, there are enormous difficulties facing researchers trying to draw causal inference from or about some pattern found in Big Data: there are almost always a large number of additional and mostly uncontrolled confounders and covariates with correlations among them, and between them and the identified variables. This is particularly the case given that most Big Data are formed as a nonrandom sample taken from the infinitely complex real world: pretty much everything in the real world interacts with everything else, to at least some degree."

In other words, when dealing with big data, which is by its very nature highly confounded, we can never truly establish exclusivity, one of the three properties of causality (Hunt, 1991). For causality to be established between two variables – x and y (where x is the independent variable and y is the dependent variable), it must be shown that only x (and a change in its values) and nothing else caused the corresponding change in y.

This discussion should not be interpreted as condemning big data, machine learning, artificial intelligence, and analytics. Rather, the discussion is aimed at recognizing their limitations. By themselves, they are important but they are not adequate to address all of the challenges now facing researchers in supply chain and operations management. If our goal, as researchers, is to address the challenges comprehensively, then we must be willing to look beyond these tools and identify other tools and approaches that may be appropriate in that they complement the capabilities offered. Sometimes, finding such tools requires us to look outside of our domain of study; in other cases, it may mean look forward for novel tools. In many cases, it may require us to rediscover tools used extensively in the past. One such tool is that of simulation.

4. Re-introducing Simulation

It can be argued that most supply chain and operations manager are concerned with establishing actions that change business processes towards some predefined measures. Good research establishes theory (an explanation) how this change happens. But to truly establish that a change was brought about by an action, the action must be turned on and off. This leads to the problem of sampling. Empirical research replicates the sample by subdividing it since we cannot go back in *real time*. Still, physical samples can never be identical. Most empirical research in supply chain and operations management does also not assess a treatment, such as in medicine or natural sciences, but remains descriptive (Bertrand & Fransoo, 2002). Simulation as method considered here, is a sampling procedure that replicates *simulation time* to generate data. This can happen in a controlled environment, and if computer with common random number streams are applied also the sample can be identical. Simulation can do so since sample and time are an abstraction, being the sample involved in a 'play' (or set of rules, model) that unfolds in time, similar to a theater or musical that creates the same past/future time and events over and over again. This play/model can be repeated as often as desired creating comparable states that can receive different treatments. This disconnection from the real world is one of its biggest strengths, but also its biggest weakness in terms of validity. Note that it also distinguishes simulation from digital twins, if the twin is defined as real time simulation. To use the digital shadow, which is created by real time modelling of a physical system, as simulation model, it needs to be disconnected from the real world and run in abstract simulation time. Otherwise, it would just replicate the real world, being a shadow. A digital twin is consequently a cybernetic control device that can use simulation, not a simulation. This also explains why we do not see digital twin as a research method in the literature, but only as applications.

Simulation is one of the most used research methods in supply chain and operations management (Shafer & Smunt, 2004). Simulation is essentially a model or representation that mirrors or copies the operation of an existing or proposed system or process. Kleijnen & Smits (2003) categorize simulations into four categories: business games, spreadsheet simulation, system dynamics, and discrete-event dynamic simulation. To these four, this paper adds a fifth category – agent-based models. Both business games and spreadsheet simulation are useful, given the premium they place upon ease of understanding and development. However, as the complexities grow, the latter three categories of simulations become more appropriate. All three are typically realized using a computer. Note, that we neglect Monte Carlo simulation, which establishes an output distribution for a given input distributions and a mathematical model, since it does not model time (being mainly applied for robustness analysis in analytical research) and most recent literature on computer simulation focusses on the other three (Borshchev, 2013).

System dynamics is essentially a set of differential equations that are solved over simulation time. System-dynamics approaches have been praised for their ability to cope with high levels of complexity (Besiou & Van Wassenhove, 2021), they are also often considered more rigorous given the underlying mathematical model, which however also limits their applicability. Discrete event and agent-based simulation use computer code and heuristics. Both model events (Chan et al., 2010), and which type of simulation is used depends on the perspective taken rather than on the model. Agent-based typically refers to modelling the agents that constitute the system, with the system emerging out of their interactions. This can often be realized with discrete event simulation software, and some discrete event simulation software adopts an agent-based approach (e.g., SimPy©). Discrete event simulation starts from the system. It is typically realized with object-oriented programming language being the main building blocks objects, such as capacity resources, with build in methods and variables. Meanwhile, there is also software that combines system dynamics, discrete event simulation and agent-based simulation (e.g. AnyLogic©). Agent-based models, which can be integrated into a system dynamics or discrete event environment, recognize the importance and impact of agents (which can be either individuals or collectives such as groups or organizations) and their behaviors. For example, Schwab et al. (2019) have combined agent-based with system dynamics modelling for simulating growth scenarios of a Swiss SME and investigating how financial performance and financial sustainability are influenced by managerial decision-making and macro-level banking regulation. Agent-based models and simulation may also be used for supporting decision-making, for example, as decision-support tools that help citizens and NGOs to fulfil their watchdog function in detecting possible misconduct in supply chains and service provision (Chesney et al., 2017).

Computer simulation is widely used and generally accepted in supply chain and operations management (Größler *et al.* 2008, Shafer & Smunt 2004) because it facilitates the study of complex systems under controlled conditions, allows for system experimentation, and permits full information data collection – conditions seldom possible in real life. Simulation is unlimited in terms of experimental design and thus the potential to explore causality and contexts. Simulation is also arguably the only quantitative research method that allows for exploring the impact of transients. Simulations are also less expensive than experiments in real life, easily scalable, and widely applied. They may also be used where real-life experiments are ethically problematic, as for instance in cases of labor exploitation and human rights violations (Gold et al., 2020) and thus represent an excellent tool for research in sustainable supply chains and operations. However, simulations are also typically seen as less rigorous than mathematical models, and less relevant for practice than empirical research. Leading supply chain and operations management journals, including the *International Journal of Operations and Production Management*, are consequently often reluctant to accept simulation studies. This might be due to the fact that computer simulations are often not fully utilized and just used as add-on to carry out comparison studies. There is a need to unlock its unique potential to contribute to theory building and to theory testing. For this we need to rethink how simulation is applied.

4.1 Empirical grounded simulation

The goal of research, when boiled down to its basics, is simple – to generate knowledge. This goal can be achieved in several different ways: identify and categorizing a new phenomenon, identify the factors associated with this phenomenon, determine the causal links between phenomenon and its associated factors. It is the latter which provides an explanation, and thus creates new theory in a narrow sense (Sutton & Staw, 1995). Following Peirce (1998), scientific inquiry is largely based on the genesis of theory (abduction), the structured design of falsifiable hypothesis or experiments (deduction), and the controlled execution of experiments to corroborate theory and utility (induction). These three kinds of enquiry build a continuous research cycle (Handfield & Melnyk, 1998), an illustration of which is given in Figure 2.

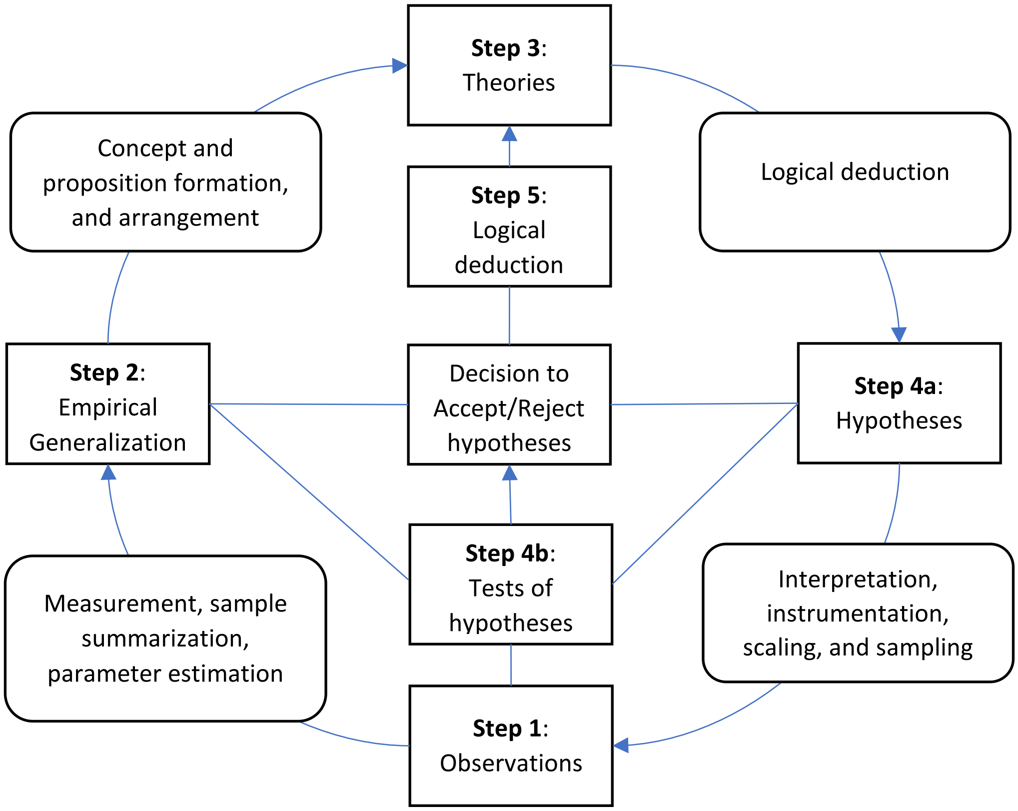

Figure 2: The Principal Information Components, Methodological Controls, and Information Transformations of the Scientific Process (according to Wallace, 1971, p. 18.)

Simulation as a method is the "perfect" vehicle for data generation. It allows for perfect control, complete reporting of data, and it is reproducible. Yet, it is simply that. Most simulation studies fail to get accepted at leading supply chain and operations management journals because they just generate and analyze data. Many authors argued for multi-method approaches combining simulation with empirical research methods (e.g., Bertrand & Fransoo, 2002; Chandrasekaran *et al*., 2018) by either building models close to practice or to test simulation results in practice. This is definitively one way of conducting meaningful empirical simulation research since, for example, findings from empirical studies (such as case studies and surveys) can be triangulated by findings from simulation research (Jick, 1979) in order to enhance the preciseness and scope of application of theory (Gold et al., 2020). But the focus is typically on the empirical part, not the simulation.

A compelling simulation study always works with four research building blocks – research question, theoretical frame, experimental design, data collection, data analysis and its interpretation – which reflect above research cycle. The objective of simulation is not to build a model that is as close as possible to reality. The objective of simulation is also not to compare the performance of different algorithms or control solutions without any further explanation. Rather the objective of simulation is to design experiments that appropriately capture phenomena in practice, thus advancing our understanding of these phenomena. Davis et al. (2007) underline that "simulation's primary value occurs in creative experimentation to produce novel theory" (p. 480). We see simulation as closely linked to intervention-based research, this is to derive new theoretical and managerial insights by engaging with practice and solving complex field problems (van Aken *et al*., 2016). As intervention-based research, simulation focuses on the application of theory to practice (Chandrasekaran *et al*., 2020). But the focus is on the development of theory (Davis et al., 2007) for observed phenomena (rather than the development of a solution for a problem) and the intervention occurs in a simulation environment. Here we also distinguish empirical simulation research from quantitative empirical research as advocated by Bertrand & Fransoo (2002), which focus on the validation of axiomatic results in real-life operational processes. Simulations provide a high degree of modelling flexibility, and unlimited experimental designs, which provides a unique means for testing causal assumptions theorized in practice. It is easy to gather evidence on how an outcome was achieved, which allows not only for testing theory (induction), but if a "mismatch" between the expectations and reality occurs, for the ad-hoc development and testing of new theory (Oliva, 2019). In fact, good empirical simulation focusses on these "mismatches", and thus the abductive element. It is when the simulation yields outcomes that do not match reality (or expectations) that new theory emerges, which leads to a continuous refinement of the theory and the model.

4.2 Simulations that establish causality

The focus on causality is central to supply chain and operations management research. For example, it can be argued that during the 1990s and early 2000s, when researchers made extensive usage of techniques such as structural equation modelling, they were interested primarily in understanding causality. But establishing causality, especially with secondary data, is not a trivial exercise. While causal inference from observational data is possible, it relies on the occurrence and non-occurrence of variables in practice, so that data for different system states can be separated, executing nature pseudo-experiments (Pearl, 2009). We do recognize the presence of "natural experiments", but we also recognize that these do not occur frequently. One is always limited to the events that have occurred and the data that has been collected. To truly establish causality, one requires some form of controlled experiment where certain factors can be introduced or dropped to determine and isolate their impact on the overall results. Simulation allows repeatedly carrying out such controlled experiments, for example in the sense of sensitivity analyses (for examples see Kunz et al., 2014; Reiner et al., 2015), thus building new theory or elaborating and refining existing theory (Fisher & Aguinis, 2017).

Testing causal assumptions is significantly different from quantifying causal assumptions. For example, deep learning is good at finding patterns but cannot explain how they are connected, which let to developments as explainable artificial intelligence. A causal assumption is typically expressed as x has an impact on y. If x is a necessary cause of y, then the presence of y necessarily implies the presence of x. The presence of x, however, does not imply that y will occur. If x is a sufficient cause of y, then the presence of x necessarily implies the presence of y. However, the presence of y does not imply the presence of x since another cause z may alternatively cause y. In order for an event y to be caused by x, x should be necessary and sufficient. This is called an active cause, which meets the three base criteria of causality (Hunt, 1991): simultaneity (i.e. x and y always occur together), precedence (i.e. x occurs before y), and exclusivity (i.e. only x --> y). A series of active causes over time results in a causal chain. Simulation that establishes causality assesses active causes and their propagation to develop theories for phenomena such as cascading failures, bullwhip effect or ripple effect (eg. Ivanov, 2017).

However, already Mill (1843) doubted that causes are truly sufficient or necessary for its effects. In practice, very often no clear cause can be identified. This is the more the case in socio-technical contexts that are of interest to supply chain and operations management. Rather events are due to a conjunction of a large number of causal factors, each one necessary but singly insufficient to achieve the outcome. This causal model can be considered an INUS condition, this is an "insufficient but necessary part of a condition which is itself unnecessary but sufficient for the result (Mackie, 1965, page 245)", which simplified reads "a necessary element in a sufficient set of conditions, NESS" (Pearl, 2009). For example, while many people may accept an electric short-circuit as an explanation for a fire, a short-circuit is neither necessary nor sufficient for causing a fire. There are fires without short-circuits and there are short-circuits without fire. However, if the short circuit is combined with the condition that there is inflammable material and no efficient sprinkler, fire occurs. So, the short-circuit is a necessary element in a sufficient set of conditions that have to be met. To actually capture this, all elements and their behavior needs to be modeled. Discrete event and agent-based simulation allows for quantifying and testing different types of causes, including NESS conditions. This is important to advance knowledge on how to avoid accidents, disruptions, quality loss or errors, for example in healthcare settings which are characterized by high complexity and multiple players (e.g., Armitage, 2009; Collins *et al*. 2014; Underwood & Waterson, 2014; Tucker & Singer, 2015).

4.3 Simulation as supplement to machine learning, artificial intelligence, and analytics

A major shortcoming of machine learning, artificial intelligence and analytics, is that they are bound to data. In practice, this data first needs to be created and using empirical data these tools are bound to retrodiction. This shortcoming can be overcome by use of simulation. For example, machine learning is a subset of artificial intelligence, which includes reinforcement learning (Rolf, 2023) and deep learning (Kusiak, 2020). While deep learning is learning from a training set, and then applies that learning to a new data set, reinforcement learning dynamically learns by adjusting actions based on continuous feedback to maximize a reward. But reinforcement learning agents cannot directly learn from the physical world. They require a virtual environment (or simulation) to allow for replication and learning through trial and error (MacCarthy & Ivanov, 2022). Similar, also training and test sets for deep learning can be created through simulation. This provides a controlled dataset, which provides more insights, and that can be replicated by fellow researcher.

For this, there is a need to develop standardized/generic simulation problems. During the 1970s, 1980s, when interest was in MRP and MRP operation, there was Factory that had been initially developed at the OSU. Identifying the minimum criteria that any acceptable job shop simulation model had to satisfy (e.g., Melnyk & Ragatz, 1989) led to broad acceptance in the community and cumulative advancement of control methods. Having a standard problem is important in two ways. First, it allows for replication and cumulative advancement of theory. Second, it ensures that the context is not fine-tuned to realize certain performance results. It should be noted that the objective is not to just use the standard model, but the standard model should be used as supplement to generalize results. It allows to identify contingency factors, i.e., contexts that change the relation between variables.

4.4. Simulation for sensitive environments

Simulation research should be based – at least to some extent – on qualitative and/or quantitative empirical data collection. Simultaneously, simulation techniques may help investigating phenomena and research settings in greater depth where real-life experiments are unethical or difficult to set up, or where extensive primary data collection is potentially dangerous, as for example when inquiring into criminal activities such as corruption (Silvestre et al., 2020) and modern slavery (Caruana et al., 2021), or socially undesirable behaviors such as opportunism in supply chains (Lumineau & Oliveira, 2020). An example is Schelling's model of segregation (Schelling, 1978). Results from this model could not have been ethically obtained otherwise.

5. Concluding Remarks

Simulation has been around for quite some time. As somewhat expected, computer simulation emerged with the advent of computers, and the first wave of computer simulation emerged with the advancement of computing power. Computer simulation facilitates the study of complex systems under controlled conditions, allows for system experimentation, and permits full information data collection – conditions seldom possible in real life. Unfortunately, most of the simulation studies do not take full advantage of this potential. Computer simulation is extensively used to show the superiority of one decision rule over another decision rule, or to quantify the effect of changes in a decision variable, but there is a tendency to not provide further explanation or analysis which limits its power for developing theory. Leading supply chain and operations management journals are therefore often reluctant to consider simulation studies. This study argued that today is the time to reconsider simulation as a viable, attractive, and highly appropriate research methodology. It is time to reconsider simulation because the world changed and the highly dynamic, complex new normal is not amendable to other quantitative methods and modern analytical tools, such as machine learning, artificial intelligence or analytics. But for simulation studies to be accepted, they have to change. We outlined four types of simulation studies that hold much promise: empirical grounded simulation, simulations that establish causality, simulation that supplements machine learning, artificial intelligence, and analytics, and simulation for sensitive environments. We refrained from outlining specific topics. We feel that simulation as a research method applies to many different topics and highlighting a restricted set would limit the contribution of our paper. Our study rather outlines certain traits of problems that are specifically amendable to simulation.

Research needs to evolve with the questions that concern management to stay meaningful. Computer simulation is the right tool for the right time and the types of problems that are now relevant, and likely will remain relevant. We therefore encourage researchers to use simulation along the lines outlined in this study, and leading supply chain and operations management journals to reconsider simulation.

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