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Decision Support

Hybrid models as transdisciplinary research enablers

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ABSTRACT

Modelling and simulation (M&S) techniques are frequently used in Operations Research (OR) to aid decision-making. With growing complexity of systems to be modelled, an increasing number of studies now apply multiple M&S techniques or hybrid simulation (HS) to represent the underlying system of interest. A parallel but related theme of research is extending the HS approach to include the development of hybrid models (HM). HM extends the M&S discipline by combining theories, methods and tools from across disciplines and applying multidisciplinary, interdisciplinary and transdisciplinary solutions to practice. In the broader OR literature, there are numerous examples of cross-disciplinary approaches in model development. However, within M&S, there is limited evidence of the application of conjoined methods for building HM. Where a stream of such research does exist, the integration of approaches is mostly at a technical level. In this paper, we argue that HM requires cross-disciplinary research engagement and a conceptual framework. The framework will enable the synthesis of discipline-specific methods and techniques, further cross-disciplinary research within the M&S community, and will serve as a transcending framework for the transdisciplinary alignment of M&S research with domain knowledge, hypotheses and theories from diverse disciplines. The framework will support the development of new composable HM methods, tools and applications. Although our framework is built around M&S literature, it is generally applicable to other disciplines, especially those with a computational element. The objective is to motivate a transdisciplinarity-enabling framework that supports the collaboration of research efforts from multiple disciplines, allowing them to grow into transdisciplinary research.

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1. Introduction

Operations Research (OR) as a discipline has its focus on improvement (Ranyard, Fildes, & Hu, 2015; Royston, 2013); hence, it has been argued that the role of OR practitioners in applied research and applications goes beyond that of an analyst, where teamwork and collaboration are integral to its application. If we accept that the role of OR professionals includes networking and orchestrating work (Batson, 1987; deTombe, 2002), then a common representation is necessary to allow for a true exchange of information to enable this role. Several scholars have attempted such an undertaking in OR. For example, Wiek and Walter (2009) proposed a transdisciplinary evaluation approach for supporting cross-sectoral, collaborative planning and decision-making. Similarly, Bammer (2018) made the case for an increasing need for strategic alliances, and recommended a set of common tools. The implementation of knowledge transfer to facilitate these tools needs to

be undertaken by the participating experts. In supply chain management, an approach with a similar intention has been provided by Ivanov, Sokolov, and Kaeschel (2010). In particular, their contributions on supply chain multi-structural composition and structure dynamics uses graph theoretic domain-agnostic formal representations to achieve an interdisciplinary understanding, ultimately allowing for a transdisciplinary common representation. Our paper is motivated by such efforts in the OR community, which have proposed approaches and frameworks to support common understanding of the different knowledge constructs, theories, and tools within disciplines, considering their combined application to support problem solving. The focus of this paper is on modelling and simulation (M&S), which is one of the most frequently used OR techniques.

Successful M&S studies rely on different groups of stakeholders working through the various stages of a simulation study. These studies may involve the development of models using a single simulation technique (for example, discrete-event simulation (DES) or agent-based simulation (ABS)), or increasingly, hybrid simulation (HS) (Brailsford, Eldabi, Kunc, Mustafee, & Osorio, 2019). Powell and Mustafee (2017) distinguish between hybrid M&S stud-

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ies and HS, the former being the application of cross-disciplinary approaches at different stages of a simulation study, and the latter being the combined application of multiple simulation techniques. A hybrid M&S study concerns the development of hybrid models (HM), but not necessarily HS models. Irrespectively, the objective of both HM and HS is to represent the system of interest better. In this paper, we extend the definition of HM, to include cross-disciplinary techniques. Cross-disciplinarity can be sub-categorised into interdisciplinary, multidisciplinary and transdisciplinary approaches that might be used for the development of HMs. These terms are defined in [Section 2](#).

In this paper, we present a conceptual framework for hybrid approaches, predominantly driven by hybrid M&S examples but generally applicable to all kinds of computational support of research. Our specific contribution is a transdisciplinarity-enabling framework that supports the collaboration of research efforts from multiple disciplines, allowing them to grow into transdisciplinary research. Accordingly, in our work, we refer to HM studies that are conducted by teams of multidisciplinary, interdisciplinary, and transdisciplinary researchers and practitioners, who apply theories, methods, and tools from their respective disciplines towards a common solution. The recent events to battle the SARS-CoV-2 coronavirus showed the need for such a formal alignment of conceptual approaches. Via computational OR approaches applied to available and necessary data, the community urgently tried to better understand the pandemic as a multi-value, multi-criteria problem. The complexity of the spread and effects of the pandemic required experts from many disciplines to work together, such as in the COVID-19 Healthcare Coalition ([MITRE, 2020](#)), which was established as a coordinated public-interest, private-sector response. This coalition brought healthcare organisations, technology firms, non-profits, academia, and start-ups together to support supply chains for critical equipment, inform coordinated social policies, and provide data driven insights to protect people, reserve the healthcare delivery system, and examine the economic effects of intervention. Many of these organisations utilised computational OR methods, including combining information from various models. One such example is the tool developed by the RAND@ Corporation, which combines information from an epidemiological model, an economic model, and a qualitative policy analysis to assess the effects of various non-pharmaceutical interventions on health and economic outcomes ([Vardavas et al., 2020](#)). However, as the organisations represent different disciplines and different schools of thought, they all focused on different facets needed to address the complexity of the COVID-19 problem space, and all used different computational infrastructure based on heterogeneous data sources and formats. Each collaboration required an often tedious and time-consuming alignment of understanding which aspect of the research was supported, which methods were applied, how the implementations had to be orchestrated, and what data mediation and alignment of the pedigree of data (an attribute of data provenance) was needed. During the pandemic, a notable effort by the UK-based Alan Turing Institute and the DE-COVID project ([DECIVID, 2020](#)) led to the development of an analytics platform to allow researchers from diverse disciplines access to real-time data from multiple NHS Trusts. As will be discussed subsequently in the paper, the integrateability of infrastructure for data exchange is a cornerstone for enabling multidisciplinary research that involves a computational element (like OR and M&S). As proposed in this paper, a transdisciplinarity-enabling framework which conceptualises the building blocks for multi-, inter- and transdisciplinary research will thus help towards the realisation of the call to action for the OR community, such as published amongst others by [Currie et al. \(2020\)](#) and [Squazzoni et al. \(2020\)](#).

As this paper is mainly written for the simulation community, we largely restrict its scope to the convergence of M&S

with disciplines such as industrial engineering, economics, OR, cyber-physical systems (CPS), and computer science; however, where relevant we make reference to intersections with other disciplines. The paper is structured as follows: [Section 2](#) reviews the literature on cross-disciplinary approaches in OR and M&S. The terms interdisciplinary, multidisciplinary and transdisciplinary research are defined in sub-[Section 2.1](#), with [Section 2.2](#) devoted to existing work on hybrid frameworks. [Section 3](#) discusses cross-disciplinary work in distributed simulation and e-Science and identifies some of the key building blocks for the proposed framework. [Section 4](#) presents the proposed transdisciplinarity-enabling framework for hybrid modelling. [Section 5](#) reflects on the value of the framework, and how it can be used to support existing cross-disciplinary research efforts.

2. Literature review

The term ‘multi-methodology’ in OR has been used to describe the combined use of two or more methodologies within a single intervention. It may refer to the combination of qualitative and quantitative methods to more effectively deal with the breadth and nuance of the real world (e.g. [Mingers, 2001](#); [Mingers & Brocklesby, 1997](#)), or to a combination of quantitative methods, aiming to combine the benefits or overcome the weaknesses of individual methods ([Howick & Ackerman, 2011](#)). [Morgan, Howick, and Belton \(2017\)](#) provided an overarching framework that examined the literature for ‘all forms of mixing methods’, enabling modellers to identify the design aligned with their perception of the problem and system. This can support cross-disciplinary work at the method level. Cross-disciplinary research was regarded as one of the strengths of early OR ([Ranyard et al., 2015](#)), and [Howick and Ackerman \(2011\)](#) found that studies mixing OR methods commonly used practitioners from multi-disciplinary backgrounds. While [Ranyard et al. \(2015\)](#) and [Ormerod \(2020\)](#) argued that expanding the toolset in OR embraces opportunities, cross-disciplinary collaborations between OR and disciplines such as data science enable shared expertise ([Greasley & Edwards, 2019](#)). Each field brings complementary skills, creating new knowledge which connects the contributing traditional disciplines.

The National Academy of Sciences report on facilitating interdisciplinary research ([National Academy of Sciences, 2004](#); pp. 30–38) identified four primary drivers of cross-disciplinarity, namely, (a) recognition of the inherent complexity of nature and society, and the inability of reductionism to cope with these challenges; (b) Exploring problems and questions that are not confined to a single discipline; (c) Growing societal problems that require a broader approach on a shorter timescale; (d) Emergence of new technologies that are applicable in more than one discipline. Simulation is one of these new technologies with the potential to support new forms of collaboration between disciplines. Simulation approaches such as DES, ABS and SD have been applied in numerous application domains. When a simulation technique is used in isolation, we refer to this as *Conventional Simulation* ([Fig. 1](#)). This can be compared to HS, which is the application of multiple simulation techniques in a single simulation study ([Brailsford et al., 2019](#)). In terms of the development of conventional and hybrid simulations, the M&S community has largely continued to look inwards (be that the System Dynamics community or Social Simulation researchers). However, there are also examples of M&S studies than have explored cross-disciplinary methods and techniques. These models are referred to as *Hybrid Models* (HM). [Fig. 1](#) illustrates the distinction between conventional simulation, HS and HM. The distinction between HS and HM is further explored in a set of two papers on a unified conceptual representation of hybrid M&S, which presents a classification of HS and HM ([Mustafee & Powell, 2018](#); [Mustafee, Harper, & Onggo, 2020](#)).

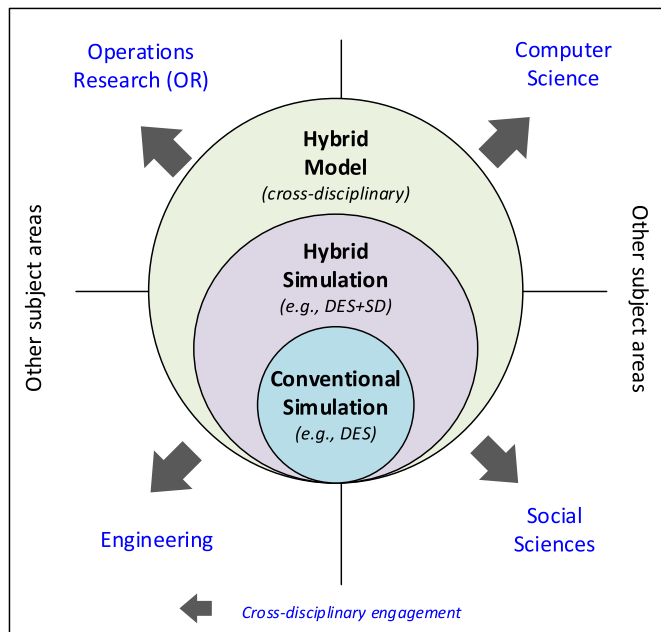


Fig. 1. Hybrid Models and its focus on cross-disciplinary engagement; adapted from Fishwick and Mustafee (2019).

All of these terms—HS, HM, hybrid M&S—and other related activities are overloaded, and the community has not converged on a common definition, as all the various viewpoints are valid and supported by practical applications (Eldabi et al., 2016; Mustafee et al., 2015a, 2017). The mix of digital and analogue simulation described by Burns and Kopp (1961) is one of the first publications to use the term hybrid. As early as the 1960s, a distinction between discrete and continuous simulation methods was commonplace (Teichrow & Lubin 1966). Shantikumar and Sargent (1983) classified four types of hybrids using simulation and analytic models. In his foundational paper on the *History of Discrete Event Simulation Programming Languages*, Nance (1993) identified HS as one of the five predominant types of simulation, defined by the inclusion of an analytical sub-model within a discrete event model (Nance defines a model that includes both continuous and discrete event components combined). More recent literature—often driven by technological developments in the tool world—refer to the mix of ABS, SD, and DES approaches as hybrids; see amongst others Zhang, Chan, and Ukkusuri (2014). Mustafee et al. (2017) recommend addressing the whole M&S spectrum as hybrid, allowing combinations on all levels of M&S categories: “Hybrid M&S results from using two or more components of different M&S categories to generate something new, that combines the characteristics of these components into something more useful for the underlying M&S effort to be supported, that are composable under the constraints of this effort.” More recently, Mustafee et al. (2020) expanded this definition to encompass cross-disciplinary HMs, which necessitate cross-disciplinary engagement between researchers and practitioners from M&S and broader fields of study. Several HM studies have used simulation with either qualitative (Soft) or quantitative (Hard) OR methods. Examples include the use of forecasting with DES (Harper, Mustafee, & Feeney, 2017), optimal packing problem with ABS (Mustafee & Bischoff, 2013), optimal coverage problem with ABS (Karatas & Onggo, 2019), use of Soft Systems Methodology and Cognitive Mapping (both Soft OR) with DES (Pessôa, Lins, da Silva, & Fiszman, 2015; Tako & Kotiadis, 2015). There are also HM studies that have incorporated techniques from disciplines such as Applied Computing, for example, DES and grid/Cloud computing (Mustafee & Taylor, 2009; Taylor et al., 2018), ABS-DES with dis-

tributed simulation (Anagnostou & Taylor, 2017), ABS with parallel computing (Montañola-Sales, Onggo, Casanovas-Garcia, Cela-Espín, & Kaplan-Marcusán, 2016). From the perspective of our research community, exploration of the extant knowledge in disciplines such as Engineering, Computer Science, Arts and Humanities, allow the identification of established research philosophies, methods, techniques and tools, which could be deployed in conjunction with computer simulation in one or more stages of an M&S study.

2.1. Multidisciplinarity, interdisciplinarity and transdisciplinarity research

The terms multidisciplinary, interdisciplinarity and transdisciplinarity are used to describe different degrees of collaboration of participating disciplines, with multidisciplinary and transdisciplinarity being the two endpoints of this comparison (Nicolescu, 2014; Stock & Burton 2011). The term cross-disciplinarity is often used to describe the alignment of vocabularies from different disciplines, creating a common lexicon that can be used in more than one discipline (Froderman et al., 2017). In this paper, we have used the term *cross-disciplinary research* to mean multidisciplinary, interdisciplinary and transdisciplinary research.

Multidisciplinary research efforts are characterised by involving “many” disciplines. Multidisciplinary teams comprise researchers from these disciplines that come together ad hoc to solve a problem that requires support from partners of the other disciplines. In such efforts, the disciplines remain mainly untouched. *Interdisciplinary research* efforts are “in between” discipline-specific methods. The disciplines remain sovereign, but they also recognise common problem spaces and shared research goals that require a more permanent form of cooperation (Lawrence, 2010). A critical review by Aboelela et al. (2007) determined the key defining characteristics of interdisciplinary research, which include a qualitative component, a common goal, and a continuum of synthesis amongst disciplines, while Collin (2009) examined a range of terms used to define interdisciplinarity, and found that integration of participating disciplines is characteristic. *Transdisciplinary research* goes ‘beyond’ the scope of disciplines by systematically integrating knowledge components into a new knowledge base, transcending the approaches of individual disciplines (Klein, 2010; 2018). It can become transgressive, as new theoretical paradigms might not simply augment, but instead substitute traditional approaches. Table 1 summarises the key defining features of these research approaches.

These definitions of multi-, inter- and transdisciplinarity, in terms of alignment of disciplines presented in Table 1, will be developed further with a specific focus on research conducted in the computational domain, such as M&S and OR (Section 3). A short review of literature on cross-disciplinary research engagement in M&S will identify the most important technical concepts (building blocks) that have enabled such successful collaboration, and will inform our conceptual framework for HM (Section 4).

2.2. Research efforts on hybrid frameworks

Within the M&S community, in particular under the research topic of hybrid approaches, several approaches have been discussed that propose a similar framework to categorise concepts of hybridisation better in support of multi-, inter-, and transdisciplinary efforts.

2.2.1. Concepts, specifications, and operations

Traore (2019) provided the following categorisation to capture concepts, specifications, and operations (Table 2). He observed that the concepts level, where the universe of discourse is set, calls for formalisms and methods to capture the required concepts in

Table 1
Key defining features of cross-disciplinary sub-categories.

Alignment of Disciplines	Cross-disciplinarity		
	Multidisciplinarity	Interdisciplinarity	Transdisciplinarity
Integration	Disciplines remain separate, but scope of methods and information increase with different perspectives. There is no integration of theoretical perspectives nor findings (Van den Besselaar & Heimeriks, 2001).	Blending and cooperation (Lattuca, 2002), but not collaboration (Klein, 2018). Bridging between disciplines, or some degree of restructuring of disciplines.	An overarching synthesis of disciplines. New methodological and theoretical frameworks, co-production of knowledge with stakeholders (Klein, 2018).
Communication Purpose	Loose or superficial, terms are mapped (Collin, 2009; Klein, 2010; 2018). Disciplines inform or contextualise each other. A central characteristic of multi-disciplinary research is that it is often application-orientated (Van den Besselaar & Heimeriks, 2001).	Mutual integration of concepts, methodology, procedures and terms. Blending methods creates permanent bridges between knowledge bases, generating new theoretical, conceptual and methodological identities (Schummer, 2004; Van den Besselaar & Heimeriks, 2001), adding cognitive and social aspects (Collin, 2009), and supporting standardised information exchange (Tolk, 2016; Tolk et al., 2018).	Systematic integration of knowledge. Orientated toward real-world problems, intervention and change, co-generating knowledge that is solution-orientated, and relevant to both practice and science (Binder et al., 2015; Lawrence, 2010; Mobjörk, 2010; Polk, 2015; Simon & Schiemer, 2015; Stock & Burton, 2011).

Table 2
Hybridisation strategies in computational frameworks (Traore, 2019).

Concepts (formalisms)	Discrete Event System Specification (DEVSS), Petri Net, Multi-Agents...	Ordinary Differential Equations (ODE), Partial Differential Equations (PDE), System Dynamics...	Operation Research methods (OR), Artificial Intelligence (AI) methods...
Specifications (models) Operations (engines)	Discrete simulation models Simulators	Continuous simulation models Integrators	Algorithms Solvers

a symbolically manipulatable way. The M&S community traditionally distinguish between discrete and continuous phenomena with regard to central time-related concepts. Qualitative and quantitative computational approaches, such as OR, or artificial intelligence methods, focus on problem-solving steps and mechanisms. Hybridisation comes at this conceptual level with the objective-driven need to deal with temporal considerations for the system under study, while trying to find a solution to the problem under study. At the specification level, the real-world system and problem under study is expressed as a model, using the universe of concepts adopted, resulting in both discrete and continuous simulation models, and problem-solving algorithms. At the operations level, engines are built to execute the model defined at the immediate upper level. Such engines are often referred to as simulators, integrators, and solvers. Operational hybridisation occurs here to support the requirement for multiple execution engines, each devoted to aspects that other engines do not support. Traore (2019) introduced an additional column with physical devices to address cyber-physical system challenges as well, which will be addressed in a later section of this paper in more detail. It is not shown here, as the focus lies on the hybrid modelling challenge.

2.2.2. Paradigms, methodologies, techniques, and tools

In Mustafee and Powell (2018), Mustafee uses Mingers and Brocklesby's (1997) definitions of paradigms, methodologies, techniques, and tools, and adapts them for hybrid studies. These definitions were purposefully inclusive of many ideas, as they were originally used to address as many methods as possible. This is also the objective in the domain of hybrid studies.

Paradigms can be qualitative (i.e. more subjective and interpretive), or quantitative (i.e. more objective, providing numeric results). Conducting simulation-based experiments provides hard results, so it falls under the quantitative paradigm. Nonetheless, in the conceptual modelling phase, the use of qualitative approaches is often supported, which results in a hybrid approach using multiple paradigms for the overall study. Methodologies are developed within a paradigm and embody its philosophical assumptions. In

the M&S domain, we distinguish particularly between the discrete and the continuous methodology. The techniques have well defined purposes within the methodology, such as the stock and flow technique used for SD, or event lists and queuing techniques for DES. Thus, tools are means to execute these techniques.

This classification scheme enables a clear definition on which level the hybrid approach originates. Multi-technique hybrids usually remain within a methodology, and multi-technology approaches remain within a paradigm. The highest form of hybrids exist at the multi-paradigm level. While the usual definitions of hybrid M&S study approaches can be covered with this scheme, it can be extended to cover other aspects of multi-modelling dimensions as well, such as all abstraction levels, facets, and phases of interest for multi-, inter-, and transdisciplinary research (Powell & Mustafee 2017). Note that different facets of the research as well as different abstraction levels address the referential aspect of the research support (Section 4.3).

3. Building blocks of the framework and the three research perspectives

In this section, we review existing work on successful cross-disciplinary research engagement in M&S. As cross-disciplinarity can be distinguished into interdisciplinarity, multidisciplinary and transdisciplinary approaches, our review of existing work will be guided by the definitions of inter-, multi- and transdisciplinary research as presented in Section 2.2. As M&S is a computational domain and often application oriented, examples of existing work will help us define the technical attributes that have led to successful cross-disciplinary outcomes. This will guide the development of our framework for HM, which is presented in Section 4. Although our framework is conceptual in nature, a discussion of the technical elements will lead to a wider appreciation of the framework.

A central characteristic of multi-disciplinary research is that it is often application-oriented (Van den Besselaar & Heimeriks, 2001). There are many examples of applications where simulation is used

to add breadth, knowledge and information to a research process, whilst retaining its separate identity. *Distributed simulation*, for example, has been applied in areas such as telecommunications, semi-conductor manufacturing, logistics and supply chains, and war-gaming, but has continued to retain its distinct identity. The integration of data and methods characterises interdisciplinary research within a common conceptual framework, such that the synthesis is different from and greater than the sum of its parts (Wagner et al., 2011). Interoperability of implementation is a key element for interdisciplinary research. The area of *e-Science* provides integrated sets of technologies, collectively known as e-infrastructures or cyberinfrastructures, which enable interoperation of simulators and other tools. However, these technologies are not mutually exclusive; for example, Taylor (2019) provides an e-Science vision for distributed simulation. Sections 3.1 and 3.2 discuss distributed simulation and e-Science as two examples that have enabled successful cross-disciplinary M&S collaboration in research and practice. Through this discussion, we identify the most important technical building blocks that could be incorporated, albeit at a conceptual level, for a framework on HM that is devoted to the computational domain. Section 3.3 discusses these building blocks in relation to multi-, inter- and transdisciplinary perspectives of research. Our conceptual framework for HM is defined by these three perspectives and their underlying building blocks.

3.1. Distributed simulation

Since the late 1970s, the field of *Parallel and Distributed Simulation* has studied approaches to distributing a simulation across many computers and linking together and reusing existing simulations running on one or more processors (Fujimoto, 2015). Co-ordinated execution of such distributed models over different computers requires specialist distributed computing software. This software is called distributed simulation middleware. There are also standards for distributed simulation, e.g., IEEE 1516 High Level Architecture (HLA) (IEEE 2010), which are implemented by different distributed simulation software. For example, Run Time Infrastructure (RTI) 1.3NG (DMSO, 1999), Service-orientated HLA-RTI (Pan, Turner, Cai, & Li, 2007), The MAK RTI (MAK Technologies, 2020), poRTIco (The poRTIco project, 2020) and Pitch pRTI (Pitch Technologies, 2020) implement the HLA standard. It is important to note that there are also implementations of distributed simulation middleware that are not specific to the HLA, e.g., Aggregate Level Simulation Protocol (ALSP) (Wilson & Weatherly, 1994), Distributed Interactive Simulation (DIS) (Miller & Thorpe, 1995), GRIDS (Taylor, Sudra, Janahan, Tan, & Ladbroke, 2002), FAMAS (Boer, 2005). In this section, we have mainly considered examples from distributed simulation practices that have used the IEEE 1516 High Level Architecture (HLA) family of standards, the de-facto standard for distributed simulation.

The HLA is a fully configurable standard developed for military training systems, but with alternative uses in mind. With its freely definable information exchange objects and time management services, HLA was developed to support general distributed simulations, with a strong vision of bringing different communities together. This enabled different disciplines to work together outside of the military community. When the National Aeronautics and Space Administration (NASA) launched simulation efforts in support of future operations, the HLA was identified as a viable option (Reid & Powers 2000). As an outreach event with the international education community, NASA provided a framework based on the HLA to bring aerospace and simulation students together (Crues, Chung, Blum, & Bowman, 2007). In annual so-called 'Smackdown' events (now called the 'Simulation Exploration Experience', or SEE for short), international groups came together with models of launchers, lunar stations, lunar mine operations, and

many more concepts of interest to NASA, to work together to address common challenges (Elfrey, Zacharewicz, & Ni, 2011). At the 2016 SEE event, Falcone et al. (2017) demonstrated the effectiveness of their domain-independent HLA development toolkit that provides a software framework (HLA Development Kit Framework [DFK]) to enable the development of HLA-based simulation models. The SEE-DFK was developed by an international multidisciplinary team that consisted of researchers in Computer Science (UK) and Electronics and Systems Engineering (Italy).

HLA has been applied to support many disciplines too numerous to capture here. Examples include healthcare (Katsaliaki, Mustafee, Taylor, & Brailsford, 2009), transportation (Schulze, Straßburger, & Klein, 1999), maintenance and repair operations (Mustafee, Sahnoun, Smart, & Godsiff, 2015b), energy systems (Menassa et al., 2013), and even unexpected fields, like demand forecasting for the fashion industry (Bruzzone, Longo, Nicoletti, Chiurco, & Bartolucci, 2013). HLA has been proven a widely applicable simulation interoperability solution with a strong technical foundation, and has been instrumental in promoting multidisciplinary work. For example, in Katsaliaki et al. (2009), the DES model was applied to the supply chain for blood, and in the context of operations management discipline it focussed on inventory management of a perishable product (blood) and distribution logistics. In this work, the HLA standard was also used to investigate the speed-up of blood supply chain models. Thus, the focus of the latter part of this work was on applied computing. This is an example of multidisciplinary research work that involved the combined application of methods, techniques and tools from multiple disciplines (M&S, applied computing and inventory/supply chain management). Similarly, Mustafee, Sahnoun, Smart, and Godsiff (2015b) proposed the use of the HLA to develop a hybrid DES-ABS simulation of maintenance, repairs and operations (MRO) for offshore windfarms. In this model, the ABS-element of the work simulated turbine failures using a degradation function, and the DES element of the hybrid model simulated MRO strategies. Distributed simulation was proposed as a mechanism for synchronised model execution and exchange of messages between the Simul8™ DES model and the NetLogo™ ABS model. This is an example of a multidisciplinary project that involved supply chain management (a topic in operations management), M&S, and applied computing (HLA-RTI).

The discussion has identified the standards, middleware and frameworks, for example SEE-DFK (Falcone et al., 2017), that have contributed to the development of distributed simulation as a sub-field of M&S and enabled researchers from different disciplines to collaborate. Abstractions that further enable cross-disciplinary collaborations have been developed. One notable example is the **SISO-STD-006-2010 Standard for COTS Simulation Package Interoperability Reference Models**, which "makes it possible to capture interoperability capabilities and requirements at a modelling level rather than a computing technical level" (Taylor, Turner, Strassburger, & Mustafee, 2012). Thus, our definition of multi-disciplinarity (Fig. 2), aimed at computational domains such as M&S, not only necessitates mechanisms for data exchange at the technical level (e.g. HLA-RTI and GRIDS) but also benefits from existing standards like the HLA, and reference models like SISO-STD-006-2010, with the latter guiding the implementation of the former.

3.2. e-Science

E-science can be defined as science that necessitates large-scale computing resources and massive data sets to perform scientific enquiry through M&S approaches; science that requires access to remote scientific instruments and distributed software repositories; and science that generates data requiring analysis from experts belonging to multiple organisations and specialists in

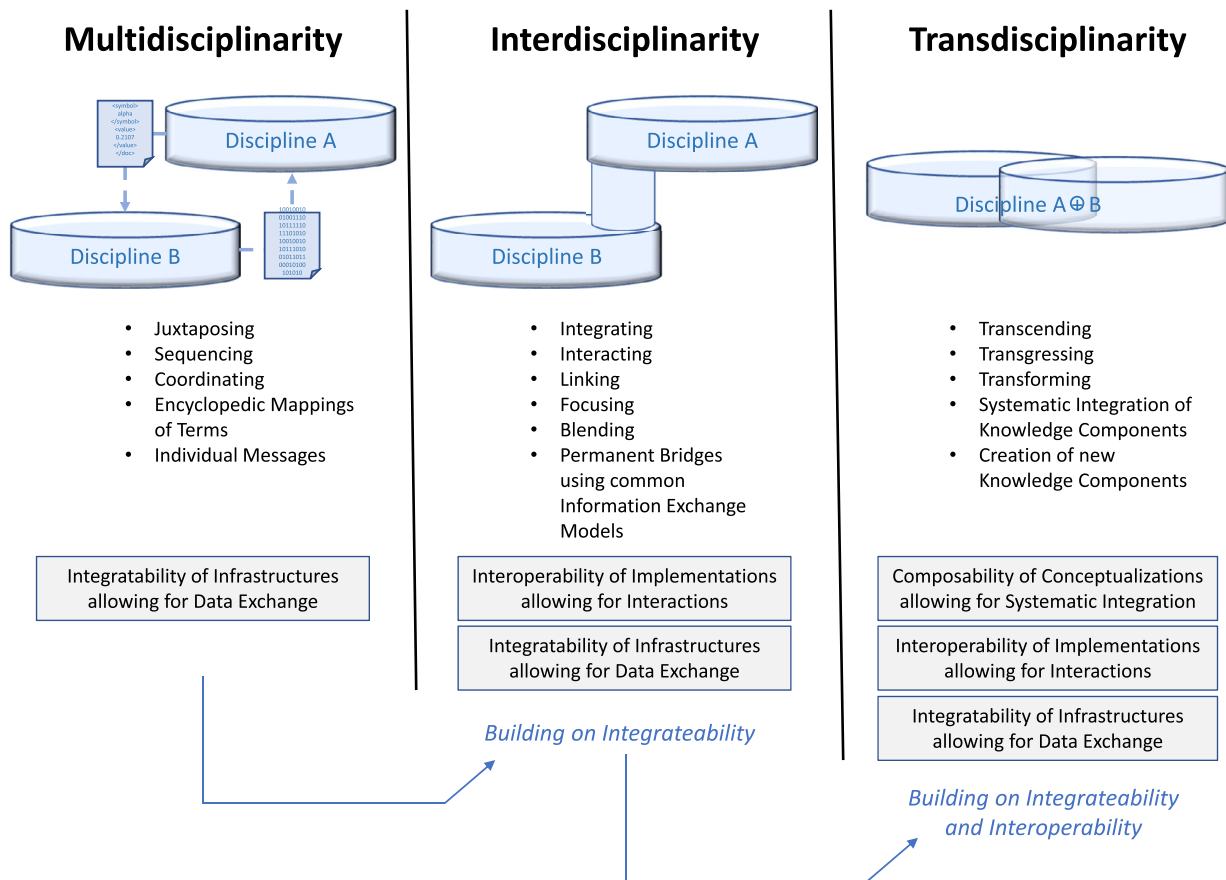


Fig. 2. Multidisciplinarity, Interdisciplinarity and Transdisciplinarity (adapted from Klein, 2014 and Tolk, 2016).

different knowledge domains (Hey & Trefethen, 2002; Mustafee, 2010). John Taylor, who was the Director General of Research Councils in the UK Office of Science and Technology, is often credited with the introduction of the term e-Science (Hey & Trefethen, 2003). Core to the growth of e-Science is the integrated set of technologies collectively known as e-infrastructures or cyberinfrastructures (Bird, Jones, & Kee, 2009)—terms that emerged concurrently in Europe and North America in the late 2000s—that are essential for high-performance simulation applications. The genesis of these technologies arguably came from the field of grid computing, a sub-discipline of computer science/applied computing. Grid computing focuses on large-scale resource sharing, innovative applications and high-performance orientation, with the objective of coordinated resource sharing and problem solving in dynamic multi-institutional virtual organisations (VOs) (Foster et al., 1998; 2001). A VO is defined as a group of individuals and/or institutions engaged in some joint task who share resources (hardware and software) by following clearly stated sharing rules. The application of grid computing technologies by scientific communities came to be known as e-Science; the VOs that drive e-science research are now commonly referred to as virtual research communities (VRCs).

There are numerous examples of publicly funded e-Science projects where M&S plays a fundamental part. Arguably, the most well-known example of a VRC is the international community of physicists engaged in high energy physics simulations that are investigating the fundamental properties of the Universe with CERN's Large Hadron Collider (LHC). The LHC project features a high-luminosity accelerator and four state-of-the-art particle physics collision detectors (ALICE, ATLAS, CMS, and LHCb). The ATLAS experiment itself has over 1700 scientific collaborators from over

150 institutions, and computing and storage resources are aggregated to provide the VRC that performs not only data analysis but also 'substantial simulation activities' (Lamanna, 2004, p1). In 2009, the LHC was supported by the worldwide LHC Grid that includes 150 computing and storage sites in 35 countries (Bird et al., 2009). Earthquake engineering provides an example of a second simulation-related e-science project. The Network for Earthquake Engineering Simulation (NEES) project links earthquake researchers across the U.S. with leading-edge computing resources and research equipment, such as supercomputers, data storage, networks, visualisation displays, sensors and instruments, and application codes. This allows collaborative teams (including remote participants) to plan, perform, and publish their experiments (Spencer et al., 2004). The Earth Science Grid (ESG) project is a further example of collaborative interdisciplinary e-science research in climatology, weather and risk assessment. In the ESG, global climate models are used to simulate climate, and experiments are executed continuously on an array of distributed supercomputers. In 2005, the resulting data archive, spread over several sites, contained upwards of 100TB of simulation data (Bernholdt et al., 2005). Another example is the GLOBal Robotic telescopes Intelligent Array for e-Science (Castro-Tirado et al., 2014), which is a web-2.0 project based on a network of robotic telescopes.

Inter-disciplinary research collaborations such as LHC, NEES and ESG usually necessitate establishing physical links among instruments and computing resources. Further, such levels of interoperability require the development of common information exchange models. One example of this is interdisciplinary research on e-Science and biological pathway semantics that is conducted under the BioPAX initiative. It has developed an ontology for pro-

viding “a common conceptualisation” for defining the semantics of biological pathway data, allows pathway interoperability, and delivers on the requirement of e-Science to support biological and life sciences research (Luciano & Stevens, 2007). Thus, our definition of inter-disciplinarily (Fig. 2) aimed at computational domains such as M&S, includes technical building blocks including permanent bridges, interoperability and a common information exchange model.

3.3. The three research perspectives

Our review of existing research in distributed simulation and e-Science has identified, at a technical level, some of the building blocks that facilitate cross-disciplinary engagement. Such engagement can be further facilitated through a higher-level of abstraction—a conceptual framework. Fig. 2 depicts the ideas for multidisciplinary, interdisciplinary and transdisciplinary efforts. Below Fig. 2, implications are listed for collaboration ability of new technologies that are applicable in more than one discipline, with the focus on simulation solutions.

For multi- and interdisciplinary research, the implications refer to the technical building blocks discussed under distributed simulation and e-Science respectively. In our review, we were unable to identify examples of transdisciplinary research in M&S (based on definitions presented in Table 1). Learning from existing literature, the conceptualisation proposes the terms *integrateability*, *interoperability*, and *composability* (Tolk et al., 2013), which are fundamental to the development of our hybrid framework. The framework can enable the synthesis of discipline-specific methods and techniques, advance multi- and interdisciplinary research within the M&S community, and serve as an enabler for transdisciplinary research.

The concept of integrateability contends with the physical/technical realms of connections between systems, which include hardware, firmware, protocols, and networks. Interoperability contends with the software and implementation details of interoperations. This includes exchange of data elements via interfaces, the use of middleware, and mapping to common information exchange models. Finally, composability contends with the alignment of issues at the modelling level. The underlying models are purposeful abstractions of reality used for the conceptualisation being implemented by the resulting systems. It is important that they provide a consistent representation of truth within all participating components. Mustafee et al. (2017) provides a view of this challenge for hybrid M&S approaches, as provided in the introduction to this paper. These concepts map well to the different disciplinary collaboration stages defined in this section. Successful multidisciplinary interoperation of solutions requires integrateability of infrastructures, so that ad hoc messages can be exchanged between the tools supporting the participating discipline. To support the continuous collaboration on common problem space that characterises interdisciplinary research, their tools have to become interoperable, so that common information exchange requirements can easily be supported, and services can be mutually exchanged and used. Finally, the transcending and transforming characteristics of transdisciplinary research require an alignment of concepts, which is the definition of composability of models.

3.1.1. Multidisciplinary research perspective

As illustrated in Fig. 2, at the technological-level, multidisciplinary is facilitated through the integration of infrastructures that allow for data exchange using different standards and protocols. In relation to M&S (computational domain), the IEEE standards for distributed simulation and its run-time implementation allow for the exchange of messages and the co-ordination of simulation time. These standards allow for the integration of not only simulators but also other computer programs, for example,

the use of inexpensive game simulators with an agent-based framework to support 3D virtual environments (Manojlovich, Prasithsangaree, Hughes, Chen, & Lewis, 2003). Here, we make a distinction between the integrateability of simulators and software artefacts. For the former, the causal correctness of multiple simulators will need to be enforced by distributed simulation software (usually achieved through optimistic or conservative approaches), but for the latter, this could be mere message exchange that triggers the coordinated execution of tools and other software artefacts. Indeed, this does not require the use of distributed simulation but could be achieved through distributed computing (socket programming and web services) and inter-process communication. There are several examples of such work where multidisciplinary research has been confined only to integration of tools, applications and the computational domain, and the development of common infrastructures for message exchange.

Considering a team of researchers who have experience and, for the sake of argument, several successes in collaborative multidisciplinary research, how could they progress to the next stage of research interaction, namely, interdisciplinary research work? In a very broad sense, in the business world, this could be akin to progressing from one stage of maturity to the next; in technology and innovation, a leap from one level of technology readiness to the subsequent level. Organisations rely on models such as the Capability Maturity Model (CMM) and the Technology Readiness Level (TRL) to guide them through these stages. Similarly, it is arguable that a model that would allow progression from multidisciplinary to interdisciplinary work would be beneficial for the M&S community and researchers from disciplines with which they collaborate. Therefore, we articulate the need for a modelling framework and propose the conceptual framework for hybrid modelling presented in Section 4.

3.3.2. Interdisciplinary research perspective

From a technical perspective, interoperability of implementation is a key element for interdisciplinary research (Fig. 2). Interdisciplinary work leverages the integrated infrastructures for message exchange (developed for the purposes of multidisciplinary research collaboration) and develops linkages across disciplines. These linkages go further than the technical interoperability of tools and applications and its slant towards the computational domain (as is the case with multidisciplinary research). In the computational domain, ‘tools’ are mostly software programs, and they are used to build ‘applications’. Tools and applications from multiple disciplines exchange data to enable multidisciplinary research. A higher abstraction from the ‘tools’ are the scientific methods that permeate scientific disciplines. For example, in the M&S community, there are tools for DES and SD. These tools implement well-established ‘methods’, for instance, discretisation of a system in the case of DES, holistic representation of a system using SD, the ABC method for DES (advance time, execute bound events, execute conditional events). Interdisciplinary research should achieve linkages at this higher ‘methods’ level, and in time this may lead to the development of tools that encompass an integrated view of the disciplines, from which new areas of research may flourish. We take the example of HS to communicate our line of argument.

Although HS is not an example of interdisciplinary research, it does share some characteristics with disciplines that exist in silos. For example, DES and SD communities have a long history of developing methods, tools and applications, without much interaction. Collaboration amongst researchers who viewed systems in two different modelling resolutions (discrete versus continuous; details versus holistic) led to early work where tools and applications were integrated to facilitate data exchange—see Brailsford et al. (2019) for a review of HS and different integration methods. However, with time, as the combined modelling work matured,

tools like *AnyLogic*TM came into existence, providing an implementation of multiple world-views and enabled hybrid modelling of continuous and discrete simulation to flourish. In this case, the integration of discrete and continuous methods enabled the development of a simulation executive, which could handle both the ABC of DES and SD continuous progression of time.

Establishing linkages between methods belonging to different disciplines should extend beyond only establishing bridges in the computational domain (as is the case with HS). Interdisciplinary research requires a common conceptual framework and analytical methods based on shared terminology and agreed goals. For example, [Yeh \(2016\)](#) evaluated the challenges of interdisciplinary climate change research, identifying conceptual challenges at the knowledge, system, and ontological levels. Likewise, [Gavens et al. \(2017\)](#) identified overlapping scientific, structural, and interactional challenges in interdisciplinary public health research, subsequently proposing a checklist for facilitating interdisciplinary research based on empirical findings. Similarly, a HM framework will help the M&S community (and collaborating disciplines) in the conceptualisation of linkages between methods in diverse application domains, and how this could be associated with both the computational domain and the different stages of a simulation study.

3.3.3. Transdisciplinary research perspective

Transdisciplinary research creates a new knowledge base through systematic integration of knowledge constructs from different scientific disciplines ([Klein, 2010; 2018](#)). From the technical standpoint, composability of conceptualisations from the various disciplines allows for the systematic integration of transdisciplinary efforts ([Fig. 2](#)). This necessitates engagement between teams of researchers and a careful design of transdisciplinary collaboration. Taking the example of a large-scale collaboration in climate change research involving 450 researchers from 40 organisations, [Cundill et al. \(2019\)](#) reported on the enablers of such collaboration. These included frequent face-to-face meetings, spatial proximity of the researchers, and commitment to achieving transdisciplinary aims and objectives of the research ([Cundill et al., 2019](#)). Other lessons from transdisciplinary research (also derived from participatory practice and collaboration between disciplines and stakeholder partners) include managing adjustments between science and practice, embracing trust, co-leadership and communication, and the reintegration of results and insights into impactful outputs ([Binder, Absenger-Helmli, & Schilling, 2015; Collin, 2009; Polk, 2015](#)).

Transdisciplinary research is associated with 'wicked problems' ([Pohl, Krütti, & Stauffacher, 2017](#)), in particular those associated with socioecological systems ([Guimarães et al., 2018; Norris, O'Rourke, Mayer, & Halvorsen, 2016](#)), health and social care ([Hiatt & Breen, 2008; Parkinson et al., 2017](#)), and education ([Salite, Drelinga, Iliško, Ojehnoviča, & Zariņa, 2016](#)). Unsurprisingly, there is significant emphasis on the barriers to applying the principles of transdisciplinary research in practice. When dealing with complex problems, the shift from disciplinarity to transdisciplinarity requires imaginative thinking as well as logical reasoning, and a clarification of definitions, goals, and methods, to enable cross-fertilisation of knowledge from diverse groups of people to increase understanding and develop new theories.

This motivates the requirement for a transdisciplinarity-enabling framework for HMs, similar to the efforts of the smart grid community ([Knight, Widergren, & Montgomery, 2013](#)), which allows the required level of collaboration to enable the migration from multidisciplinary approaches to ultimately transdisciplinary research. Our focus lies with simulation solutions, HM and simulation studies of every type, as captured in the collected studies of [Balaban, Hester, and Diallo \(2014a, 2014b, 2015\)](#).

3.4. Summary

Discussions in [Sections 3.1 and 3.2](#) have shown that the existing multi- and interdisciplinary efforts in M&S have primarily focussed on the integration of tools and applications, such as exchange of messages, sequencing and coordination, interoperability and integration ([Fig. 2](#)). However, transdisciplinary M&S research requires the holistic association of research ideas, theories, concepts and methods from diverse disciplines, from which emerge new tools, applications and new ways of problem-solving. Similar to the **SISO-STD-006-2010 Standard for CSP IRM**, and which "makes it possible to capture interoperability capabilities and requirements at a modelling level rather than a computing technical level" ([Taylor et al., 2012](#)), the objective of the framework is to propose a higher level of abstraction, to serve as a common language among researchers from diverse disciplines in debating the necessary considerations for developing multi-, inter- and transdisciplinary HMs. A conceptual framework for hybrid modelling would serve the following purposes:

- Enable researchers working predominantly within M&S and seeking cross-disciplinary collaborations to engage in a structured approach combining discipline-specific theories, methods and tools towards the development of a HM.
- As multidisciplinary is facilitated through the integration of infrastructures, the framework should provide the means for data exchange among tools and applications that belong to different disciplines. Our framework therefore includes the integration of tool and applications at the multidisciplinary level ([Fig. 5- the inner oblong](#)).
- As interdisciplinarity is characterised by continuous collaboration among participating disciplines, the framework should allow tools and applications to become interoperable so that common information exchange requirements can easily be supported, and services can be mutually exchanged and used. This is usually achieved through the development of common methods ([Fig. 5- the middle oblong](#)).
- As transdisciplinarity is characterised as being transcending and transforming, the framework should allow for the composability of conceptualisations, thus allowing for systematic integration. Such integration is usually only possible through the development of a transdisciplinary body of knowledge, which necessitates working towards common research questions and the development of explanatory frameworks and theories ([Fig. 5- the outer oblong](#)).
- The framework is instrumental in seeking inter- and multidisciplinary that goes beyond just the integrateability and interoperability of tools and applications from the computational and application domains, towards the conceptual alignment of methods.
- It should serve as a transcending framework for the transdisciplinary alignment of M&S research with domain knowledge, hypotheses and theories from diverse disciplines. This leads to the development of new composable methods, tools and applications and new ways of doing research.

Our framework for hybrid modelling is described next.

4. Transdisciplinarity enabling framework for hybrid models

Disciplines usually comprise two different focus areas. The first focus looks at the science behind the discipline, dealing with the general principles that build the foundation of the discipline, also known as 'the body of knowledge'. The second is more interested in finding general methods and solution patterns that can be applied to various problems in the field of interest. They are obviously connected, as methods have to be rooted in general

principles to be sure that they will lead to the desired outcome, and new solution patterns may lead to new insights and help to discover new general principles. In the next subsections, we will evaluate these areas of focus for hybrid modelling challenges, with particular interest in the implications for a transdisciplinarity-enabling framework.

4.1. Methods, tools, and applications

Methods, tools, and applications are terms that are often used together to demonstrate mutual support as well as different emphases. They are all grouped around the general methods and solutions patterns of a project. We define them as follows:

- Methods are procedures and techniques capturing a regular and systematic way to conduct an analysis and guide a process of enquiry, including the desired interactions between those involved (Ormerod, 2018).
- Tools are implementations supporting the application of methods. If the nature of the method allows it, tools can implement the method itself in some cases, leading to its automisation. In the context of this paper, we are predominantly interested in computational tools, such as computer simulations.
- Applications are focused use of methods and tools to solve a particular problem, also referred to as solutions.

As discussed in Section 2.2, methods are often grouped into methodologies, which build a system of related alternatives that postulate how to conduct discipline-specific procedures. As they also display a common pattern of solving a problem class, they are sometimes referred to as paradigms. As simulation solutions are predominantly considered as computational tools by other disciplines, helping them to make better decisions that are technical or managerial in nature, the work of simulation experts often focuses on this area. Different modelling methodologies are applied to serve the viewpoints of the supported domains, and different model types are developed to implement the various different mathematical concepts, for example, different classes of differential equations.

Many of the hybrid modelling and simulation cases discussed in Section 2 are covered by methods, tools, and applications, as their focus is to provide the best computational support possible to the hosting discipline, such as mixing discrete and continuous solutions and tools, or even methods, resulting in a better support of the user by the hybrid approach. Approaches to combining methods in OR, such as Total Systems Intervention (Flood & Jackson, 1991), multi-methodology (Mingers & Brocklesby, 1997), the Transformation Competence Perspective (Ormerod, 2008), and the toolkit of mixed-method designs (Morgan et al., 2017) directly address the issue of choosing the methods and tools needed to support the chosen approach to finding a solution.

However, it can be challenging to identify common solutions and reusable approaches when the focus is the computational support of various disciplines that are separated by different languages and terms, different concepts and procedures, and by different topics of interest, as stated earlier in this paper. These shortcomings are continuously addressed when disciplines conduct multi-, inter-, and finally transdisciplinary research, but as long as disciplines are separated by the principle of reductionism and specialisation, only some commonalities in the supported disciplines will support alignment. It is therefore necessary to establish a scientific area of focus, as we will do in the next section.

4.2. Research, theories, and methods

As the topic of our paper is the support of cross-disciplinary research, we put the research first, followed by theories and meth-

ods. Their commonalities are the general principles that build the foundation of the discipline. We understand the terms as follows:

- Research refers to the collection of theories that are part of the body of knowledge, also comprising the researchers and organisations applying such theories and knowledge to conduct research.
- Theories are substantiated explanatory frameworks for a series of facts that are testable and can be used to explain past and predict future observations.
- Methods are procedures and techniques that capture a regular and systematic way to accomplish something, that are derivable from and consistent with a set of theories.

We use the term 'research' instead of 'discipline', as this allows us to include organisational aspects. The topic of research is defined by the discipline, topics of interests and the supporting theories. However, organisational and human aspects are often as important for collaboration as the possibility of aligning supporting elements captured in theories, methods, and tools, as captured by Knight et al. (2013) for the collaboration between energy providers, energy consumers, and regulators in a future Smart Power Grid environment. They observed that the alignment of tools and methods via standards was much easier to accomplish than the development of mutually agreed and supported business processes by the different stakeholders. Similarly, for researchers of a potential cross-disciplinary research effort, Gardner pointed out: 'From an organisational perspective, the challenges facing interdisciplinary collaboration are voluminous in the literature, including issues related to existing organisational and reward structures, disciplinary socialisation, and resulting impediments to communication across disciplinary cultures' (Gardner, 2013, p. 243). Toward addressing this issue in M&S studies, participatory efforts have been proposed as an effective tool to bring cross-disciplinary research teams together in theory-building efforts (Luna-Reyes et al., 2019). This transcends the alignment of methods and tools, toward solution-oriented, co-generated knowledge.

Theories should be easier to align, as it should be generally possible to capture them in form of ontological structures. Tolk et al. (2013) presented a case study that successfully aligned reference models, defined as 'explicit model(s) of a real or imaginary referent, its attributes, capabilities, and relations, as well as governing assumptions and constraints under all relevant perceptions and interpretations' (Tolk et al., 2013, p. 71). These were models of multiple participating research partners conducting transdisciplinary research on the effects of rising sea levels and the effectiveness and costs of possible countermeasures. They also showed how to derive a consistent model from this reference model and to derive simulation tools to help answer various research questions. As simulation methods themselves have different theoretical bases and underlying assumptions, Lorenz and Jost (2006) argued that aligning purpose, object characteristics and methodology are important early considerations for modelling solutions. This corresponds with the alignment of research and methods. Theories are sited between the two, supporting generalisable solutions and an understanding of limitations (Clanon, 1999; Rebelo & Gomes, 2008).

Some disciplines may comprise theories that are not consistent with each other. Examples are well known from physics, where theories describing gravitational physics and those describing quantum mechanics are contradictory. In the case of the natural sciences, the application domain and validity constraints are often well documented, so that decisions about which theory to use to derive methods and tools are well understood. In other fields, such as the social sciences, theories often represent different schools of thought, and are often not as precisely formulated as needed for ontological modelling (Davis, O'Mahony, Gulden, Osoba, & Sieck, 2018). In any case, the rigorous modelling of theories facil-

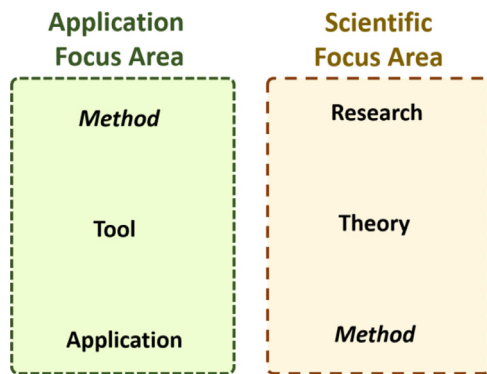


Fig. 3. Application and Scientific Focus Area Components.

itates understandable, reproducible, replicable, reusable, and credible research. The discipline of M&S is still struggling to accept its own theory. Zeigler's foundational work (Zeigler, 1976; Zeigler & Muze 2018, 2000) addresses many facets, but emphasises the application area of focus more than the theoretical and disciplinary challenges. Nonetheless, this foundation provides sufficient means to describe methods, concepts, and paradigms as well as resulting tools and applications in a consistent, formal way that also allows the evaluation of their combination into hybrid approaches.

The synergy between theories, methods, and tools underlies any field of human endeavour that builds knowledge, as illustrated by the synergistic approach for conducting mixed-methods or cross-disciplinary research proposed by Hall and Howard (2008). The synergistic approach has three defining dimensions: a set of core principles, a conceptual framework for delineating the practical and contextual aspects of doing research, and a model that represents the interaction between the core and conceptual dimensions of the approach, both within and across disciplines. Similarly, Ormerod (2018; 2019) described how *inquiries* are at the centre of theory and logic in OR. His 'pragmatic OR method' describes the links between the research and organisational domain, the methods, and the application. For cross-disciplinary work, the methods within each discipline establish the link between application and scientific focus areas discussed in these subsections, as illustrated in Fig. 3. As indicated by Tolk et al. (2013), it is possible to provide a consistent mathematical framework that unambiguously describes and mediates research questions, supporting theories, derived methods, and implementing tools. The transdisciplinarity-enabling framework must provide the same stability.

Nonetheless, hybrid modelling has to address specific M&S challenges as well. These are already a challenge in standard application, as the challenge of how to ensure composability described in Section 3.3 is still an open research question. When addressing multiple disciplines, the importance of clear and unambiguous support for aligning research, theory and methods becomes increasingly important.

4.3. Methodological and referential aspects

Hofmann, Palić, and Mihelcic (2011) evaluated the use of ontologies within the M&S domain. They introduced the distinction between *methodological* and *referential* ontologies, driven by the observation that models are conceptualisations of (real world) referents, and computer simulations are executable expressions of these conceptualisations. Thus, computer simulations are manipulations of arbitrarily chosen symbols referring to objects that are conceptualised from a specific point of view for a specific purpose, such as a research question or training task. While other software engineering disciplines develop a product that supports a real-world referent directly, simulation develops the support of a

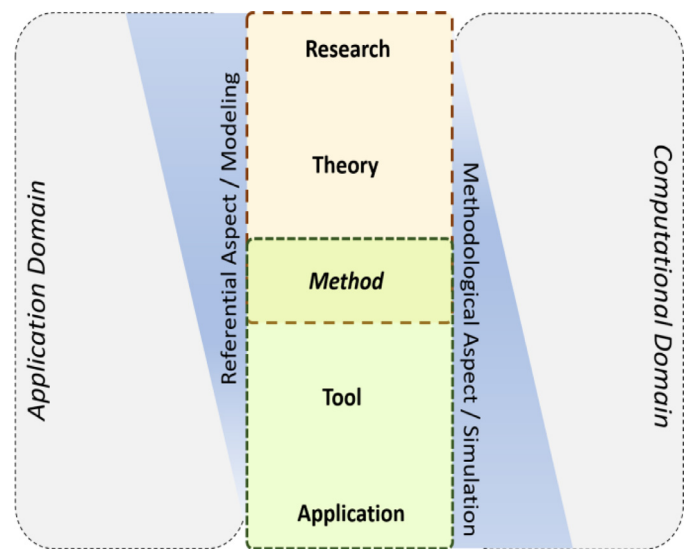


Fig. 4. Transdisciplinarity-Enabling Framework for Hybrid Models.

conceptualised referent within a model that acts like a substitute for reality. In other words, we provide 'sufficiency theorems' that provide, under the correct constraints and rules, the desired observable structures and behaviour expected from the real-world reference (Axtell, 2000). As a result, referential ontologies are needed that capture these conceptualisation results, assumptions, and constraints to address the question 'What is modelled?' in a given simulation solution.

In contrast, methodological ontology answers the question 'How is the model simulated?' It allows the capture of modelling paradigms regarding modelling methodologies (such as DES, SD and ABS approaches) and model types (such as ordinary differential equations, process algebra, and temporal logic), as discussed, amongst others, in Fishwick (2007). This methodological aspect has been the focus of many simulation interoperability studies, as the referential aspect was often perceived to belong to the supported discipline that applied simulation as a computational tool to provide a specific solution for a discipline-specific question. As a result, the sharing of research results is often impeded by the different taxonomies and business processes of the supported disciplines. The lack of a common way to capture the supported discipline in the form of a methodological ontology becomes a significant obstacle for the reuse and sharing of research results. Research, theory, methods, tools, and applications must therefore address both methodological and referential aspects of the approach. Fig. 4 presents the resulting view on the various aspects of a transdisciplinarity-enabling framework.

The referential aspect borrows heavily from the application domain to be supported by the modelling efforts, but it cannot simply reuse their approaches and concepts. The HM must not only build a bridge between the concepts of the application domain—their executable expressions—it also must be a mediator between the discipline and variations in scope, structure, and resolution of conceptualisations used in their theories. The alignment of analytical OR methods with simulation solutions also falls into this realm.

In the same manner, the HM will utilise computational domain concepts and procedures when the tools and applications are dealt with. Aligning discrete and continuous simulation methods falls into this realm. If the research requires the integration of non-computational elements (such as analogue components or other physical devices), an alignment needs to happen at the tool/application level based on their domain constraints. Using the definitions of multi-, inter-, and transdisciplinarity, Fig. 5 illustrates the parts covered by the framework.

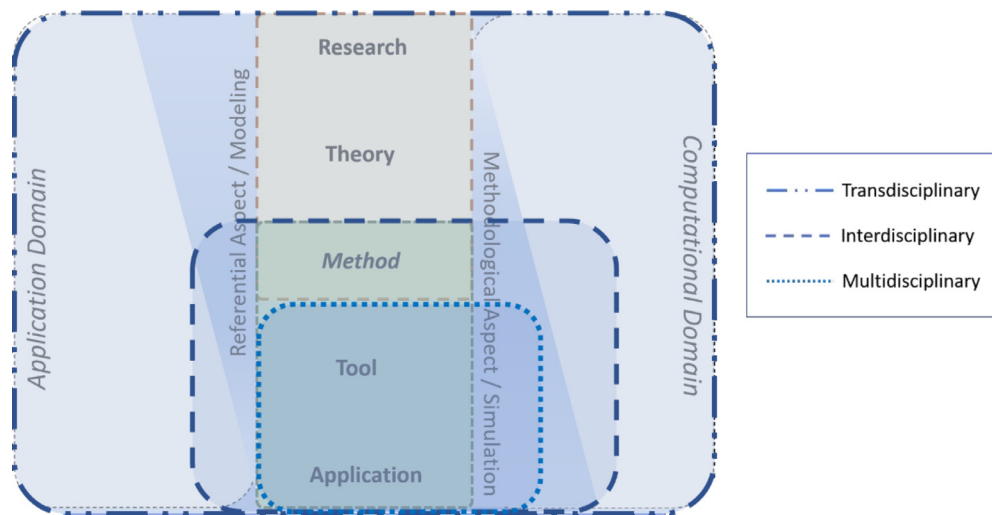


Fig. 5. Hybrid Modelling Framework supporting Multi-, Inter-, and Transdisciplinary research engagement.

The inner oblong in Fig. 5 shows the areas of support regarding multidisciplinary activities. Researchers focus on the use of tools or simply the exchange of results. Common infrastructures for this exchange are a main concern. The middle oblong extends this area to develop a common method to address the topic of interdisciplinary interest. In contrast to multidisciplinary work, a permanent, conceptual kernel to understand the problem is part of the research. Finally, if the general understanding of the problem and its context are captured by establishing a transdisciplinary body of knowledge, the framework is utilised to its full potential.

While the transdisciplinarity-enabling framework for hybrid modelling as a whole is a new concept, a survey of the literature shows that important parts of this idea are established and supported already (see Section 2.2). For example, examining theories of integration between technology and decision-makers, Burger, White, and Yearworth (2019) articulated the distinction between methodological and referential ontologies, and the need for transdisciplinary research for data-driven decision-making applications. While these theoretical perspectives may aid with developing awareness of how decision-making arises in sociotechnical relations, successful HMs will require all elements of our framework to be addressed.

5. Importance of the hybrid modelling framework for emerging transdisciplinary application areas

Transdisciplinary alignment describes the integration of domain knowledge, hypotheses and theories from diverse disciplines. This leads to the development of new composable methods, tools and applications and new ways of doing research. Transdisciplinary research is challenging for a number of reasons, as previously described; however, a key aspiration is to share a common language and representation for communication and collaboration. We now briefly examine four examples of emerging application areas, which are examples of interdisciplinary work moving toward transdisciplinary applications, and reflect on how our transdisciplinary-enabling framework can be used to support these applications. With reference to Figs. 4 and 5, CPSs are increasingly well integrated at the research and theory levels, but lack formal rigour at the method and tool levels. Computational social science formalises social science theories, which are generally complete and coherent for their purpose. However, for formal specification, challenges can arise, as can converting the results back into a shared language across disciplines for integrated knowledge. M&S studies which incorporate theories of human behaviour share the same

challenges. Finally, an area that is demonstrating a rapid increase in research and practice is that of circular economy (CE) and sustainable supply chains. Here, where a large number of disciplines must come together to formulate a problem, specify a research question and support the development of a referent model toward a computer model, work is still required at the levels of cross-disciplinary research engagement to support transdisciplinarity and model composability. These research areas are discussed in more detail in the following subsections. We end this section with a reflection of cross-disciplinary challenges in the recent management of the global pandemic, lessons learned, and the implications for our transdisciplinary enabling framework.

5.1. Integrating human behaviour in simulation models

M&S of human behaviour integrates a set of ideas and methods from areas such as economics and psychology. This enables a more rigorous approach when addressing behavioural issues in M&S, for example using laboratory and field experiments of individual and team decision-making, behaviour and human judgement. The increasing ability to model assemblies of interacting intelligent agents in agent-based modelling is opening up new avenues for research (e.g., Arango-Aramburo, van Ackere, and Larsen, 2016; Robertson, 2016), however these are often focused at the application, tool, and method levels. For example, Brailsford and Schmidt (2003) observed that collaboration with cognitive psychologists would have improved their behavioural model by refining the equations and collecting empirical data. The challenge for M&S practitioners is to follow the methodological standards established within other disciplines to prove the quality of their work in both OR and collaborating disciplines (Becker, 2016). Juxtaposing mono-disciplinary methods and keeping roots in fragmented disciplines may fail to achieve the goal of coherence and integration of knowledge. A common transdisciplinary language ensures a common referential ontology, however for both disciplines, at the methodological level it could be recognized that, despite the fact that a given conceptual tool is being used, other perspectives may increase knowledge or understanding of the problem from a different viewpoint. Our framework can provide such support by clarifying how conceptual alignment can be achieved in order to implement this computationally.

5.2. Cyber-physical systems

We understand CPS as a new generation of systems with integrated computational and physical capabilities that can interact

with humans through many new modalities (Baheti & Gill, 2011). This definition includes many different application domains, including robotics and autonomous systems (Hodicky, 2017), the Internet of Things (IoT) (Miorandi, Sicari, De Pellegrini, & Chlamtac, 2012), Industry 4.0 (Xu et al., 2016), and others.

Simulation is the computational capability used within CPS to make predictions and projections whenever a decision has to be made. The mapping of any information from the outside world to create situational awareness for the CPS is based on models of the environment. As such, the methods of M&S are pivotal to make CPS 'smart'. As CPS are characterised by many new modalities and domains, different modelling paradigms and resulting heterogeneous solutions exist, as CPS utilise diverse methods in support of their computational needs. Furthermore, even conducting a literature review on the topics of hybrid modelling and HS for CPS can be challenged by the many poorly aligned terms and interpretations used in both communities.

The National Institute of Standards and Technology (NIST) established the CPS Public Working Group to bring a broad range of CPS experts together, helping to define and shape key characteristics of CPS in an open public forum. Their objective was to manage development and implementation within and across multiple "smart" application domains better, including smart manufacturing, transportation, energy, and healthcare (Griffor, Greer, Wollman, & Burns, 2017; Mosterman & Zander, 2016). The resulting CPS Framework, an organised presentation of a CPS analysis methodology, provides a valuable conceptual framework, using meta-modelling to capture different approaches in a common description; however, it lacks the formal rigour in modelling and simulation specific considerations. Our framework can help to address this shortcoming.

Because CPS will continue to grow as a main application field for hybrid methods, this will enable the orchestrated use of hybrid methods and tools to allow for composable solutions as envisioned in Mustafee et al. (2017). This will help the CPS community to increase the extent of their collaboration to become a truly transdisciplinary effort and to maximise its impact. Thus, the transdisciplinarity-enabling framework can facilitate the necessary discussions.

5.3. Computational social science

The modelling of human behaviour in social systems emphasises the advantages and limitations of M&S. Modelling is used for developing a more precise understanding of the social system under study, and discovering connections which may otherwise remain undiscovered, such that the consequences of theories in a simulated society can be explored (Gilbert & Troitzsch, 2005). Diallo, Wildman, and Shults (2019) outlined steps required for humanities scholars, social scientists and engineers to work together to tackle complex social problems. As social science theories are implicitly a model, they are often capable of formalisation to the point that they can be implemented in a computer and run over time as a simulation, making explicit the models implicit in the theories or propositions. Expressing theories and propositions as explicit computer models can be challenging, requiring careful specification to ensure the theory is complete and coherent to translate the referential aspect to the methodological aspect. Reducing conceptual modelling to a formal model is a significant challenge for all involved disciplines at the method level. Under-specified theories, variables and mechanisms are a significant conceptual drawback (Lemos, 2019), and are often due to a deficiency of communication.

These approaches are early in their application, and few examples exist of robust, valid computational social science applications. However, in focus, computational social science is inter-

disciplinary work heading toward a transdisciplinary effort, and the transdisciplinarity-enabling framework can be used to facilitate framing the overall approach, assisting researchers in addressing the challenges at the theory, method, and methodological levels.

5.4. Sustainability and the circular economy

Simulation techniques such as DES (when used as a decision support tool in OR research and practice), have mainly focussed on productivity and efficiency-related KPIs in their analysis of outcome. However, with sustainability and the CE becoming increasingly important for businesses, it is arguable that existing KPIs must also include metrics that are specific to the triple bottom line—society, environment, and economy (Fakhimi, Mustafee, & Stergioulas, 2016). The identification of a sub-set of CE KPIs might be straightforward, as it is based on the challenges commonly faced by business (for example energy consumption, disposal and/or reuse of waste water, and recycling of waste) that use KPIs such as energy usage, CO2 emissions, and water footprint. However, for the fuller appreciation of the CE concept and for the purposes of whole system redesign, it will be important to engage in transdisciplinary research in environmental toxicology and environmental impacts, civil engineering (research in built environment and new technology), urban planning, research in recycling and reuse, workforce scheduling, risk management, economics, routing and logistics (Ivanov et al., 2010; Jaehn, 2016). This requires significant transdisciplinary effort alongside a growing interest in exploring the relationship between a CE and data-driven approaches. Here, a deeper knowledge and understanding is required to comprehend how data acquired from digital technologies can unlock the potential of a CE, by identifying new models of material use and value creation (Charnley et al., 2019).

To date, CE research remains centred in engineering and sciences, with little focus on cross-disciplinarity in circularity implementation (Okorie et al., 2018). In this inherently complex research area, which potentially involves multiple disciplines and stakeholders, problem situations are likely to arise where the specification (which drives the purpose of the model and its corresponding simulation) is not universally agreed. This challenge is apparent in interoperability and composability as the conceptualisation of the reference model becomes the reality for the simulation. Composability of models addresses the question of whether the assumptions and constraints of two conceptualisations are consistent, or whether the resulting model of combining conceptualisations remains consistent (Tolk et al., 2013; 2011). Across multiple disciplines, resolving inconsistencies can be a challenge, yet to have a successful simulation study, we must answer the modelling question to the satisfaction of the end-user, where specifying a problem is a reflection of a perception of reality. To specify and solve the right CE problem, the transdisciplinarity-enabling framework can facilitate discussions about identifying the key stakeholders, end-users, and intended use of the model toward a composable solution.

5.5. Coronavirus pandemic

In the early months of 2020, the world started to feel the effects of a daunting pandemic. Starting from China, the coronavirus COVID-19 infected people in Asia, Europe, the United States, and the rest of the world. Scientists worldwide started to address research needs to provide better decision support for politicians on all levels of government, including OR and M&S experts (Currie et al., 2020; Squazzoni et al., 2020). One of the more famous studies, documented in Ferguson et al. (2020), led to the recommendation to lock down many problem zones, including whole

countries. The use of computational means to support OR evaluations was not without criticism and warning about wrong expectations (Siegenfeld, Taleb, & Bar-Yam, 2020). One quickly realized requirement was that of transparency of the models used, their assumptions and constraints (Barton et al., 2020), as discussed in Section 4.3.

However, what became even more obvious than the need for transparency was the need for inter- and transdisciplinary teams. The COVID-19 pandemic quickly turned out to be a multi-value, multi-criteria problem with a complex solution space, in which focusing exclusively on one criterion quickly resulted in significant new problems in others. An example is the shut-down of elective surgery in hospitals to reduce the reproduction of the virus by minimizing the contact rate. Social scientists could have argued early that this may lead to a panic reaction in the population, including fear of attending emergency services, resulting in more people dying at home. Comparably, economists could have warned that cancelling elective surgery will result in financial trouble for hospitals, as this is one of their main sources of revenue. Other economic effects of COVID-19 are described by Ozili and Arun (2020). The RAND Corporation published a dashboard that allowed analysis of the effects of non-pharmaceutical intervention on health and the economy, using a common population model (Vardavas et al., 2020), but a common OR based decision support tool helping to visualize the multi-value, multi-criteria challenge was not developed. Instead, legions of dashboards were published focusing on individual part solutions.

One of the main reasons for this fragmentation is the divergence of the many collaborating disciplines. As discussed in this paper, experts from health, epidemiology, economics, social science, humanities, political science, and many more have their own tools derived from their unique methods rooted in their theory underlying the discipline. A hybrid modelling approach motivated by the framework could avoid the nearly Babylonian confusion of these many experts trying to work together. A holistic approach that addresses all layers identified in the proposed framework can ensure better collaboration, and at least interdisciplinary progress, in the event of another pandemic.

The COVID-19 Healthcare Coalition started as a multidisciplinary effort with many individual, point-to-point solutions. The need of local decision makers, such as federal agencies, governors, and mayors, to have a comprehensive presentation of all insights, options, and possible effects of interventions quickly led to the development of dashboards. These first used coordination and sequencing as a multi-disciplinary approach, but over time evolved into the use of common data, allowing the models to interact and the applications to be integrated into a coherent dashboard, which combined multiple OR approaches, supported by artificial intelligence and machine learning components, to contribute their solutions. Some of these alignment efforts resulted in standardisation efforts, in particular at the data level, to ensure that these time-consuming efforts in the future can be avoided.

Using the definitions proposed in this paper, the coalition did not reach the transdisciplinary stage, but that more than 1000 members could self-organize their research from a highly heterogeneous multidisciplinary effort to a mostly interdisciplinary effort, shows not only the feasibility, but also the clear benefit of hybrid approaches based on a common framework, as recommended in this paper. In the example of fighting the pandemic, this is measured by the highest metrics to show benefit to the community: number of lives saved.

6. Conclusion

The terms multidisciplinary, interdisciplinarity and transdisciplinarity are often confused and used interchangeably, but they

have clear definitions, as recently compiled by Klein (2010; 2014; 2018). As described in more detail in relation to simulation by Tolk and Ören (2017), a discipline covers many aspects within professional academia, including researchers contributing to a body of knowledge captured in a set of complementary—and sometimes competing—theories. They collect and archive scholarly work that contributes to the body of knowledge and develop methods that make theoretical ideas applicable for practitioners, who can apply these methods, often implemented in tools, to provide real-world solutions.

Hybrid models are playing a central role in research that combines the collaboration of more than one discipline. Disciplines are defined by their research domain, theories, and methods from a scientific focus, as well as by methods, tools, and applications from a more applied focus. Being situated in the realm of methodologies and methods, HMs are not only pivotal as mediators between the disciplines, they also connect the scientific area of focus with the application area of focus. Hybrid theoretic approaches are reflected in the HM as well as hybrid tool use, and multi-scope, -domain, and -resolution challenges within as well as between the disciplines. They provide insight into methodological as well as referential aspects of interdisciplinary work and the support with computational tools.

The proposed transdisciplinarity-enabling framework has been designed to identify components that need alignment to provide multidisciplinary and interdisciplinary M&S teams with integrateable and interoperable tools and applications, respectively. Further, it supports looking beyond only tools and applications, to focus on the integrateability and interoperability of methods in different stages of a simulation study. For example, the use of Soft OR methods to capture the requirements of a simulation study (Powell & Mustafee, 2017), such as the application of participative and facilitative approaches, for example Soft Systems Methodology in the problem conceptualisation phase of a simulation study (Kotiadis & Robinson, 2008; Kotiadis, Tako, & Vasilakis, 2014). Finally, our framework reflects the transcending and transforming characteristics of transdisciplinary research through composability of conceptualisations and methods. These will be based on new hypotheses and theories that reflect the integrated and enriched knowledge base of the various research domains.

Our framework provides a common reference architecture to support the necessary alignment between disciplines. Currently, even experts collaborating in the field of hybrid M&S are divided by a plethora of different terms and definitions. Homonyms and synonyms contribute to this confusion. The proposed framework can provide some structure and can be refined, if necessary, to address greater detail where needed. It should be pointed out that whilst the framework enables collaboration, it is not an enforcer. If disciplines do not want to conduct common research, or if their knowledge base has no overlap, as they cope with different domains, the framework will not provide the conceptualisations necessary to develop integrated, interoperable, or composable cross-disciplinary solutions. However, the framework may help to identify related concepts, either as different facets on the same abstraction level or on different levels of abstraction, like micro- and macro-structures of a problem domain, and guide disciplines to capture such relations in a structured way that allows the application and reuse of such findings.

The examples of multi- and interdisciplinary M&S research discussed in Section 3 are neither complete nor exclusive. They merely provide examples of cross-disciplinary research in various stages of alignment already being conducted today in highly relevant areas. Although most of the examples focus on methodological aspects of the tool and applications, they also show the feasibility of HMs as well as the necessity of continuing to converge our understanding of such processes to higher levels of abstrac-

tion; for example, a move from low-level (tool and application-specific) to high-level (concerning methods and concepts) integration and interoperation. Thus, our transdisciplinary framework also encourages multi- and interdisciplinary research exploration. Not all cross-disciplinary M&S engagement needs to be transdisciplinary. However, future work could examine existing hybrid applications to determine whether weaknesses in study designs could be strengthened through application of the framework. While Section 5 explored this at the domain level, evaluation of case studies against the framework could, for example, determine where lack of alignment at the application, tool, method, theory or research levels have reduced opportunities for real-world impact. For instance, poor alignment, particularly at the higher levels, can lead to a lack of stakeholder trust in M&S solutions and outcomes (Harper, Mustafee, & Yearworth, 2021).

Our framework for hybrid modelling will increase the credibility and efficacy of conjoined approaches for future research, including but not limited to M&S of the next generation of the IoT (D'Angelo, Ferretti, & Ghini, 2016), edge and fog computing (Gupta, Vahid Dastjerdi, Ghosh, & Buyya, 2017) and symbiotic simulation for Industry 4.0 (Onggo, 2019). These cross-disciplinary efforts require conceptualisations and toolsets that are no longer based on methods resulting from the era of reductionism, but require holistic views that HMs can provide. Our framework will support the development of such HMs in the future. Future research could involve the development of a set of guidelines to enable the reporting of cross-disciplinary research efforts in the M&S community, similar to the guidelines developed for strengthening the reporting of simulation studies (Monks et al., 2019).

Disclaimer

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