COMMUNICATION
Journal Section

A Call for Consensus on the Use of Representative Model Worlds in Systems Engineering and Design

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Funding information
National Science Foundation Grant Nos. CMMI/EDSE 1841192 [ZS, EG], 1841062 [JP], and 1841109 [PG].

Systems engineering and design (SE&D) researchers increasingly tackle questions at the intersection of technical and social aspects of complex systems design. Practical challenges of access, limited observation scope, and long timescales limit empirical study of SE&D phenomena. As a result, studies are typically conducted in *model world* settings abstracted from the real world, such as behavioral experiments with student subjects. Model worlds must be representative of the phenomena being studied to ensure insights generalize to the real world settings. Currently, there is a lack of shared understanding and standards within the SE&D research community to evaluate representativeness of model worlds. This Communication captures the results of ongoing efforts to build consensus on this topic: it defines the concept of model worlds, disambiguates representativeness from related concepts, and draws comparisons to other research domains. It outlines a potential path forward and calls for community participation in establishing shared standards for model world representativeness in SE&D research.

KEYWORDS
Research methodology, design experiment, representativeness, validity.

1 | INTRODUCTION

The Systems Engineering and Design (SE&D) community increasingly tackles research questions that span both technical aspects of the design of large-scale complex engineering systems and social aspects of the engineering teams doing the design. This class of problems poses challenges for empirical and theoretical study because it typically involves hundreds of engineers, collaboration across organizations, and work over multi-year periods. To overcome these challenges,

Abbreviations: DOF, degree of freedom; NASA, National Aeronautics and Space Administration; SE&D, systems engineering and design; SME, subject matter expert many SE&D researchers find a middle ground between empirical field observation and theoretical modeling, turning to what we are calling *model worlds*—laboratory experiments, observed training simulations, serious games and computer experiments—to tractably observe and experimentally manipulate phenomena of interest.

Different *model worlds* abstract the real world in different ways (e.g., students working on simplified tasks versus experienced engineers engaging in a day-long training exercise), and these differences have strong implications for which kinds of insights generalize to the real-world phenomenon of interest. We contend that the SE&D community lacks shared standards for assessing whether a *model world* is sufficiently *representative* of a real world phenomenon to enable valid *generalization*. Rather than converging towards shared standards, we observe increased fragmentation across the community which fundamentally limits our ability to aggregate knowledge and build on each other's research.

This Communication takes a modest step to move the community towards shared standards. Over the last year, the author team established an ad hoc working group to address *model world representativeness* in SE&D research. A first round of community discussions identified a need to clarify several core concepts documented in this Communication to facilitate convergence in the ongoing discussion. This Communication is organized as follows: Section 2 defines the problem we aim to address; Section 3 defines the *model world* construct; Section 4 reviews how the terms *representativeness* and *generalizability* are used in the literature; Section 5 synthesizes our proposed definition of *representativeness of model worlds* and the unique challenges associated with it in SE&D research as an open call for contribution.

2 | THE NEED FOR MODEL WORLDS

Empirical study of socio-technical systems poses significant practical research challenges due to limited access, large observation scope, long timescales, and context dependency. For example, spacecraft design organizations involve hundreds to thousands of people working together over multiple years, embedded within organization-specific cultures; furthermore, each spacecraft design problem exhibits a unique set of contingent features with respect to specific technical and programmatic challenges and constraints. As a result, phenomena associated with design organizations, artifacts, and processes are difficult to study using direct observations of the real world. At the same time, the governing socio-technical processes also challenge the limits of existing theoretical modeling frameworks.

Some researchers supplement partial observation with archival analysis and retrospective interviews following a case study methodology; [1] however, each case is labor-intensive, limiting the number of instances that can be observed. There is a strong incentive to find or build proxies for the real phenomenon—what we call *model worlds*—that enable more tractable observation and experimental manipulation. Model worlds range from theoretical models [2] to simulated environments in laboratory settings [3] to field settings. [4,5] While differing significantly in realism, fidelity and level of abstraction, all model worlds aim to be *representative* of real-world phenomena with respect to the specific research question posed.

Assessing model world representativeness is fundamental to producing generalizable results when observation of a model world replaces direct observation of the real world. Generalizability is a necessary precursor to aggregating knowledge across studies. Other fields have agreed-upon standards for *when* a model world is representative of *what*. For example, aircraft designers regularly adopt model worlds to aid in the early stages of design. Rather than building and instrumenting wings of many shapes and sizes and flying under a range of flow conditions (a huge expense), the accepted convention starts with a reduced-order, in many cases, two dimensional (2-D) model shown in Fig. 1. However, in adopting this kind of model, which abstracts many features of the real world, it is critical to understand the conditions under which it is (and is not) representative. In this specific case, a 2-D model is good for understanding airfoil performance (lift, drag, moment) for high aspect ratio wings. However, because it assumes an infinitely long wing, it breaks down for low aspect ratio wings. For these types of wings, the airflow over wing near the tips is an important driver of performance, so a 3-D model with a realistic wing length is needed in the analysis. In other words, a 2-D model is only representative for high aspect ratio wings.

Can researchers use model worlds in SE&D research settings in the same way that reduced-order models are used in aeroelasticity? We believe the answer is yes, at least for some phenomena of interest. In asking this question, it is important to realize that aeroelasticity did not start with the 2-DOF model; rather, it was synthesized over many years of research. Equally important, its utility hinges on knowing where it works and where it does not. To that end, our long-term goal is for the SE&D community to identify and promulgate model worlds and establish associated consensus on the extent and limitations of their representativeness with respect to phenomena of interest. The following sections define features of the constructs that underlie this vision.

3 | THE MODEL WORLDS CONCEPT

We define a *model world* as an *abstraction* of the real world that *represents* ***subject(s)*** *performing* ***task(s)*** *in* ***context*** for the *purpose* of advancing research objectives. Each aspect of this definition is intentional and merits additional explanation.

First, a model world must *abstract* some aspect of the real world. Abstraction allows observation and experimentation without directly impacting a real-world system. For example, the 2-DOF aeroelasticity model world abstracts an airfoil to a small set of mathematical parameters. In contrast, a field case study of a design team performing normal work in context is not a model world because it observes an instance of the real world.

Second, the model world must include the *subject of study* (either animate or inanimate), the *task* it performs (or function or process in the case of inanimate subjects), and the *context* in which that task is performed. One of the distinguishing features of SE&D research is that both context and task are important determinants of a subject's behavior. For example, a designer (human subject) performs an engineering analysis (task) differently depending on what tools and colleagues they have access to (context). Analogously, an airfoil (inanimate subject) generates different lift profiles (task or function) depending on the flow conditions (context).

Third, the model world must be used to advance specific research objectives. The representativeness of a model world only has meaning with respect to a defined research question. A model world that is representative for one objective might not be representative of another depending on how the subject, task, and context have been abstracted.

Model worlds can either be adopted or constructed. Adopting a model world involves finding one already in existence: observing subjects performing tasks in a context abstracted by others for a non-research objective (that aligns with the researcher's objective). For example, Joseph et al. leveraged spacecraft concurrent design studies, which are performed for various non-research purposes, as a model world setting to study how experts interact and share information during a conceptual design process.[6] Figure 2 shows subject matter experts (SMEs) working on a study at the Goddard Space Flight Center.[7] The subjects are real experts and their task is similar to normal spacecraft design activities but co-located in the same room for a compressed one-week timeline. This abstraction enables direct observation of the design process but also changes how the SMEs behave, both in terms of how they interact and what design choices they make.

Other examples of adopted model worlds in SE&D research leverage settings such as training simulations and engineering analogs. Gralla et al. leveraged training simulations in the humanitarian operations context to study realistic subjects working on contained but otherwise realistic tasks in a simulated environment.[4] Palma and Mesmer study how drama troupes put together a play as an abstraction of the systems engineering design process.[8] Adopted model worlds can also be viewed as natural experiments across multiple instances. In our first example, NASA's concurrent design facilities conduct hundreds of design studies per year.

Constructing a model world involves creating a synthetic environment to interrogate a research question. The researcher must choose how much and at what level of fidelity the subject, task, and context must be present to achieve representativeness. While there are established norms for abstracting features in the context of simulation, [9] adding human subjects presents additional challenges to induce realistic behaviors in an artificial setting. [10] Different model worlds may be required to address different research objectives.

For example, Grogan and de Weck constructed tabletop board games to model federated space systems. [11] Human subjects of varying levels of expertise interact with highly abstracted tasks (e.g., playing cards and chips) with interactions and context framed by game rules. While the spatial-temporal dynamics are highly abstracted, the tabletop format elicits rich interpersonal interactions suitable to study strategic design behaviors. Alternative model worlds based on computer-based simulations allow more realistic spatial-temporal dynamics but limit study of emergent social interactions around the table. In the context of railway systems, Meijer concludes that some applications, such as engaging with actual operators, require model worlds with high correspondence to real infrastructure, timetables, and processes while other applications, such as prototyping, benefit from low-tech model worlds with more flexible roles, rules, and resources. [12]

Model worlds are important research tools because they allow researchers to study phenomena when it is inefficient or infeasible for direct observation. The real world instance may be inaccessible due to confidentiality or security concerns; intractable to collect simultaneous observations of thousands of geographically-distributed engineers; absent of counterfactual or future states for comparison if the goal is to assess a novel intervention or plan for future behaviors in a new operating environment; or impossible to experimentally manipulate for ethical or practical reasons. However, since model worlds are, by definition, abstractions, it is critical to characterize when the inferences made in a model world generalize to the real world it proxies.

4 | RECONCILING REPRESENTATIVENESS AND GENERALIZATION

Representativeness is a homograph that means slightly different things across communities, posing challenges in interdisciplinary settings. This section explains three uses of the term representativeness from statistical, analytical and ecological perspectives illustrated in Fig. 3 and clarifies how they relate to generalization in SE&D research. Across disciplines, there are many other words for closely related concepts, including validity, verification, validation, and transferability. Treating each of them in depth is beyond the scope of this communication, however throughout the below discussion, we highlight some of the connections across disciplines.

Statistical representativeness describes whether inferences made about characteristics of a sample generalize to the population from which it was drawn. [13] Research in this paradigm focuses on inferring population-level characteristics. For example, a researcher might study how often or when engineers call a colleague to request design information versus seeking the same information by looking up a value in a shared database. They conduct their research by surveying engineers in a large company. The notion of *statistical representativeness* defines how they should sample and the extent to which they can generalize their findings. If they distribute their survey to all design engineers (or a random subset thereof) and the response is uncorrelated with the target phenomenon (e.g., there is no reason to believe that only good designers responded to their survey) *statistical representativeness* indicates sample-level inferences can be generalized to the population of all engineers in the firm. However, statistical representativeness does not directly support inferences about design engineers in general; this is a question of *analytical representativeness*.

Analytical representativeness describes whether theory developed by studying an empirical instance (often a case study) generalizes to other similar instances. [14] Research in this paradigm focuses on understanding causal mechanisms of a process in context. Continuing the previous example, the researcher may hypothesize that trustworthiness of information sources in each context contributes to preferences for calling a colleague or looking up data in a database. They decide to conduct their research by interviewing a selection of engineers across multiple firms. The notion of *analytical representativeness* defines how they should choose the firm cases and what those choices mean for generalization. If trust is an important moderator of preference, they should choose a few firms where engineers trust the database and others where they do not. After conducting in-depth interviews with several engineers from each organization, they can compare patterns of behaviors across instances. If engineers in high-trust organizations behave similar to each other but different from engineers in low-trust organizations, conclusions support the hypothesis that trust drives the observed behavior. Analytical reasoning supports generalizing this result to other high- and low-trust organizations, regardless of whether they were included in the study sample. Thus, analytical representativeness requires a logical argument for which features of the context-subject-task interaction are important to generate the studied behavior.

Statistical and analytical perspectives consider when (i.e., under what conditions) it is appropriate to generalize from one real world instance to another. However, model worlds are not real world instances. Whether they are created or adopted, abstraction in model worlds introduces a different set of concerns for representativeness and generalization. The key question when designing a model world to address a research question (and associated theory) is what features of the real world phenomenon need to be "expressed" for representative behaviors to emerge? These ideas are discussed most deeply in the fields of experimental psychology and behavioral economics. There is a related discussion within the simulation community, as well. Here, we extend the core ideas of *representative design* and *ecological validity* from the Brunswikian perspective that most directly relate to model world representativeness in SE&D research. [15,16]

Ecological representativeness describes whether a subject's response to stimuli in an artificial setting such as an experimental laboratory (or analogously simulation model) corresponds to their behavior in the associated real world setting (i.e., their ecology). Research in this paradigm focuses on isolating causal effects in terms of stimulus response. Continuing the previous example, the researcher may want to explain how engineers establish trust in a data source. They decide to design an experiment where subjects perform design tasks that require information from other disciplines, with differential costs of querying a database versus calling a colleague. Experimental manipulation varies how the two sources are presented with respect to trustworthiness cues. The notion of *ecological representativeness* defines which features of the real world need to be included in the laboratory setting to defend against threats to generalization.

In particular, researchers must recognize that their subjects may have ingrained assumptions, developed over long experience in a context, that are outside of experimental control. For example, engineers selected from low-trust settings may assume that database data is always out of date, regardless of the cues provided by the researchers. If not considered, this may be a serious confound (e.g., if engineers from low-trust settings perceive the cues in the experimental manipulation differently than do engineers form high-trust organizations). On the other hand, this reality can be leveraged, e.g. by selecting subjects from high- and low-trust settings proportionally to their existence in the real world, and letting their experiences serve as cues. Compared to working with student subjects who do not have the ingrained assumptions, this design enables a higher behavioral realism because the ingrained assumptions more closely stimulate realistic behavior than would any artificial cue in the lab.

Ecological representativeness enables researchers to generalize findings from the experiment to the real world that the experiment represents, but not necessarily to other real world settings. The extent to which findings generalize to other contexts is based on a logic similar to analytical representativeness. In the experimental context, the key question is about how closely cues were tailored to the particular ecology. Since the same cue can be effective for one population and not another, there is often a tradeoff between behavioral realism of the specific subjects and relevance to other settings.

Figure 4 synthesizes the concept of *representativeness* for SE&D research from the three perspectives. The statistical view drives how to generate a sample from a population to ensure sample characteristics can be generalized to the population. The ecological view focuses on what features of the world need to be represented in an experiment to cue realistic behavior so causal mechanisms can be transferred back to the real world. The analytical view establishes a logical argument to select empirical instances that are sufficiently related that explanations of phenomena observed in one setting can be transferred to other similar settings. As will be discussed in the section that follows, aspects of each of these concepts are important to defining model world representativeness.

5 | TOWARDS SHARED STANDARDS ON REPRESENTATIVE MODEL WORLDS

Advancing the use of model worlds in the SE&D community requires researchers to know which inferences can be appropriately generalized from a model world to other contexts and the community to agree on how to assess valid generalizations in studies. To that end, this section summarizes several key concepts to achieve that vision.

First, we introduced the concept of a *model world* as an abstraction of the real world that represents subjects performing tasks in context for the purpose of generalizing research insights. It is important to distinguish partially artificial settings from true empirical ones, because of the need to consider issues related to ecological validity in addition to analytical and/or statistical representativeness. For example, even if the subjects and tasks are real but the context is abstracted (as in concurrent design settings), the behavior may only be ecologically representative of some phenomena (such as design heuristics) and not of others (such as communication, due to the compressed space and time).

Second, we disambiguated three established definitions of representativeness from the social sciences. Combined, they establish a basis for mapping laboratory observations to real world SE&D contexts. Ecological representativeness relates behavior observed in a laboratory setting to a real world instance. Analytical representativeness relates one real world instance to others based on theoretical similarity. Statistical representativeness relates information from a discrete sample to its larger population. A combined progression selects analytically similar instances to study, designs or adopts a model world as an abstracted settings in which to study behavior, and samples subjects from a population.

Third, we highlighted the importance of the three-way subject-task-context interaction in driving the representativeness of models worlds in SE&D in particular. The social science fields surveyed to support this work focus on how a human (or larger group of humans) behave and whether that behavior transfers to other instances. In some fields such as experimental psychology, subject-task contingency leads to a need to control for (or at least account for) prior experiences. In other fields such as economics, the subject-context interaction emphasizes differential response to incentives based on subjective value. In SE&D research, all three of subject-task-context must often be considered to generate realistic responses, even when the focus is indeed the human. Engineering is a contextual field—manifestation of a designer's expertise is related to many factors including the design problem, available tools, and navigation of knowledge networks within an organization.

Initial community discussions also highlight that many SE&D researchers study non-human subjects which fit the framework but in a less straightforward way. Research on topics such as optimization methods, control, and design principles focus on artifacts (algorithms, methods, tools) as inanimate subjects performing a task or function in a context. Nonetheless, although it is rarely framed as such, the choice of decision heuristic in an algorithm is a representation of the subject's behavior and how they interact with their context while performing a task. For example, design researchers often choose between exploring solutions spaces using a top-down optimization framework or a bottom-up multi-agent framework. The choice of modeling framework is salient if the research goal is to mitigate computationally-intractable problems [17] or to understand how design activities are influenced by differential control and partial information availability, even if both approaches yield similar solutions. [18] This illustrates the importance of making conscious choices to select appropriate model worlds that enable transfer of knowledge to real world settings; and the framing of research choices around the subject-task-context triplet can support that conscious research design choice decision-making.

While these concepts outline what is needed to assess model world representativeness, there is much more work to do before any implied standard can be directly applied to SE&D research. As currently stated, there is substantial art to implementing notions of analytical and ecological validity, particularly as subject-task-context interactions become more complex. Our hope is that by defining key concepts and terms carefully we can initiate an important discussion.

Arriving at shared standards of model world representativeness is a long-term goal that will take community-wide contributions and discussions. In the near-term, acknowledging that representativeness is important will promote a discussion of it in studies that adopt or create model worlds. Justifying representativeness includes a statement of why a model world is appropriate for a research question and the limits of how it should be used. Even if there is room for debate in a particular context, including a rationale for peer review will lead researchers to thoughtfully select model worlds that yield greater insights. If such norms are used widely, we will also benefit from a community-wide discussion of appropriate uses of and designs for model worlds.

ACKNOWLEDGEMENTS

This material is based upon work supported by the National Science Foundation under collaborative Grant Nos. 1841192 [ZS, EG], 1841062 [JP], and 1841109 [PG]. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author and do not necessarily reflect the views of the National Science Foundation. The authors also thank Paul Collopy, Rich Malak, Anna McGowan, and Josh Summers for helping to frame this discussion, and, for their contributions to the discussion, the participants at the roundtable on "Model World Representativeness" during the NSF Engineering Design and Systems Engineering Workshop held at Purdue University in October 2019 and the audience at "Seeking wind tunnels and scale models for SE&D research: a panel discussion" during the IISE 2019 Annual Conference in Orlando.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

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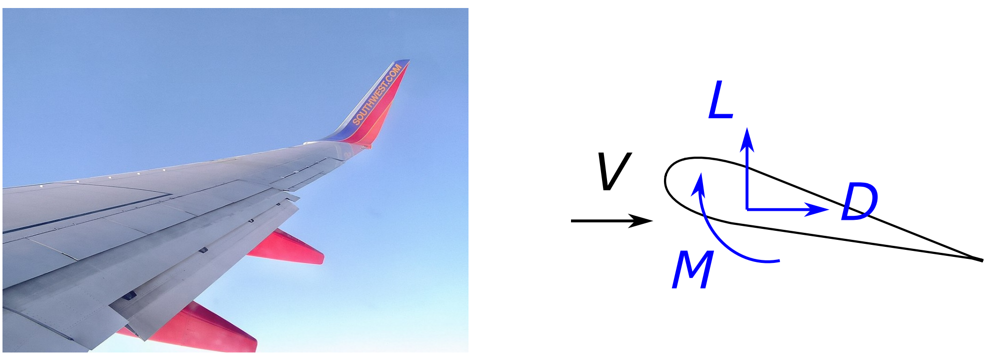
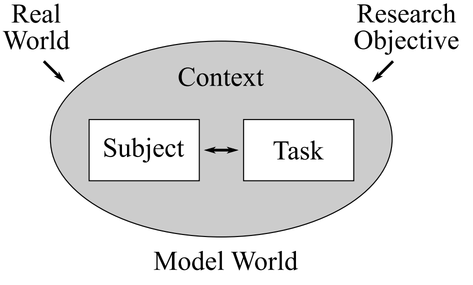


(a) Real World Airfoil

(b) 2-D Model Airfoil

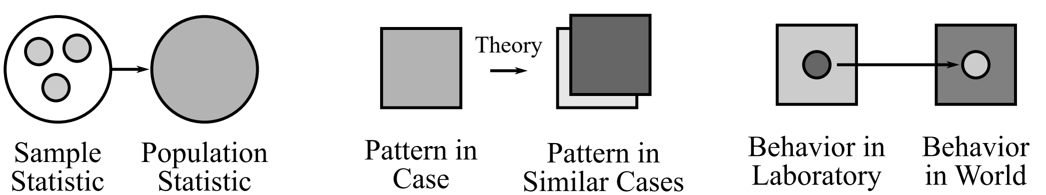
FIGURE 1 A 2-D airfoil model world represents a wing (left) as a simplified shape (right) with air velocity (V), lift (L), drag (D), and moment (M) parameters. (Image source: Wikimedia Oblivion8000/Public domain).



(a) Elements of a Model World

(b) GSFC Integrated Design Center Study Session

FIGURE 2 Left: SE&D model worlds consist of subjects performing tasks in a context; Right: A concurrent design facility is an adopted model world for spacecraft design because the task and subjects are abstracted from normal practice (Image source: Hihn et al.[7]).



(a) Statistical Representativeness (b) Analytical Representativeness (c) Ecological Representativeness

FIGURE 3 Comparison of permissible generalization under different views of representativeness.

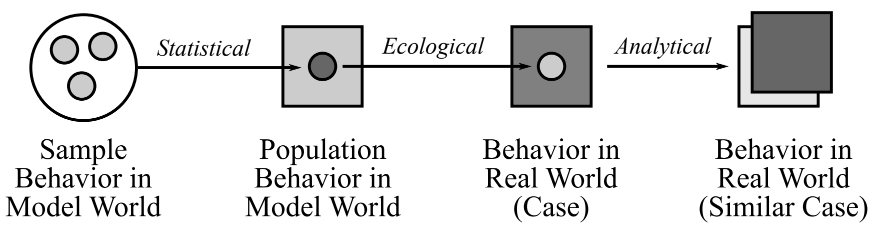


FIGURE 4 Combined view on representativeness in SE&D research settings.