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The analogical roots of agent-based modeling in economics and social sciences: the case of innovation dynamics

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ABSTRACT

Agent-based modeling (ABM) is a simulation technique which has been increasingly integrated into the economic discipline in order to understand complex systems. However, most of everyday research activities rely on the researchers' consensus concerning practical choices about modeling strategies, computational boundaries under scrutiny and the extent of empirical validation. Particularly lacking are reflections on the semantic construction of conceptual models. The paper reviews existing theoretical frameworks leading to the understanding of ABM as a technique where the cognitive processing instantiated by the instrument is distributed across different modeling layers, including conceptual, algorithmic and computational. These layers can be interpreted as an interlinked set of analogies. Then, the paper introduces a framework for assessing ABM conceptual adequacy and tests it on two families of models in the economics of innovation field.

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1. Introduction

Agent-based modeling (ABM)[1] is a simulation technique involving autonomous individual entities that behave according to a defined set of rules (e.g. Bonabeau, 2002; Grimm et al., 2005; Railsback & Grimm, 2019; Secchi, 2022). Characterized as computationally intensive (e.g. Casini & Manzo, 2016), this technique enables researchers to model interaction dynamics by designing constituent units (Bonabeau, 2002), generating patterns unforeseen analytically (Humphreys, 2004) and investigating emergent behaviors in complex systems.

Given these features and the extensive degrees of freedom granted to modelers, economics increasingly integrates ABM into its toolkit. In particular, the economics of innovation field, with its prevalence of non-linear patterns and emergent phenomena, is especially well-suited to employing this simulation technique to investigate both empirically grounded targets (e.g. Zhang & Vorobeychik, 2019) and highly idealized contexts (e.g. Fagiolo & Dosi, 2003; Gilbert et al., 2014).[2] Despite the growing success of ABM in economic and social modeling, questions remain regarding its theoretical underpinnings (see e.g. the detailed review of Anzola, 2021). Notably, some studies underline the contrast between practitioners' discipline-specific interpretations of ABMs, and the struggles faced by these models to establish an independent niche in the broader simulation philosophy landscape (Anzola, 2021). Moreover, other works offer a more critical view of the epistemic value of ABMs in the social sciences, including economics (e.g. Arnold, 2014, 2019), which has been balanced by the

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growing literature on the validation of ABMs with empirically grounded targets (Casini & Manzo, 2016; Fagiolo et al., 2019). Yet, the same possibility to validate highly idealized simulation models, whether generalized or targetless (Weisberg, 2013), can leave room for contestation (e.g. Arnold, 2019; Šešelja, 2021).

The present work aims to develop a method for evaluating the theoretical consistency of ABMs in the economic and social sciences. In doing so, it seeks to enhance the understanding of the methodological and epistemic roles of abstraction and generalization in these models. To achieve this, two key aspects must be addressed. First, it is necessary to identify the root causes of epistemic challenges, including how various dimensions of a model influence its development and how the functional orientation of ABMs impacts their structural design. Second, a robust theoretical framework must be established to rigorously assess how these dimensions interact to shape the model's overall structure and function.

The study is therefore divided into two parts. The first part systematically presents a novel analogical framework for interpreting ABMs. It begins by identifying and critically reviewing existing epistemic positions on ABMs, while re-contextualizing previous works within the theory of models and Computer Simulations (CSs) (e.g. Alvarado, 2021; Giere, 2002, 2007, 2010; Knuuttila, 2021b; Morrison, 2015; Nersessian, 2002). Based on this background, we interpret ABM as a technique where the cognitive processing instantiated by the instrument is distributed across different modeling layers, including conceptual, algorithmic and computational *constituents*.[3] This approach breaks ABMs' morphology down and, by analyzing the interaction among the constituents, enables us to investigate the process of meaning generation in ABMs as an interlinked set of analogies. Consequently, a general analogical framework is introduced, integrated into the structure of ABMs, which supports three key epistemic concepts: (a) model *adequacy*, (b) model *credibility* and (c) the method of *conceptual reconstruction* (see Sections 2.1.2 and 2.3.2). The second part applies the method of conceptual reconstruction on a specific case study engaging with two prominent families of models within the economics of innovation field, the *Simulating Knowledge dynamics in Innovation Networks* (SKIN) and the *Schumpeter Meeting Keynes* (K+S).

2. The analogical framework of ABMs

This section aims to sketch a comprehensive tool for evaluating ABM theoretical consistency. To reach this goal, the outlined method requires, above all, to be theoretically sound itself (Durán & Formanek, 2018). Therefore, the section is divided into three parts. Section 2.1 begins by reviewing the main positions in the philosophy of ABM with a focus on the central epistemic challenges that involve model construction, assessment and interpretation. In doing so, we also include those characteristics, already framed in the context of theory-of-models and CSs literature, that have become particularly challenging within the ABM literature.[4] Then, Section 2.2 examines the structural composition of ABMs and the inferential processes required to integrate their constituent layers, thereby enabling the extraction of meaningful conclusions from them. Building on that, Section 2.3 contextualizes analogical inference within the previous investigation as a possible solution to some of the issues and problems introduced and presents the proposed evaluation methods.

2.1. The epistemic and representational challenges of ABM

Challenges in the philosophy of ABM are rather unique (Humphreys, 2004), as are the frameworks developed to face them.

In their simplest form, ABMs involve a plurality of agents, each following a set of rules that govern their interactions over a given time period. Information about the resulting interaction is then stored and analyzed. Crucially, there are no limitations beyond the choices made by the modeler,[5] on the one hand, and the material constraints of the computational devices used, on the other.[6]

Moreover, the generated dynamic is usually deemed interesting only as long as it is capable to tell something about a target object. Despite that, ABMs' own logic figures as a blank page since modeler's choices shape both the kind of reference required and the nature of the boundaries of the chosen target. Modeling requirements such as customs, practices and benchmarks have been derived within the epistemic communities according to purposes, target realism, modeling strategies and constraints imposed by material substrata of targets and simulations.[7]

These layered constraints highlight two main challenges faced in the epistemology of ABM. First, the resulting model must denote and accurately represent its target in relevant aspects, allowing for a meaningful transfer of understanding. However, this requirement is both a necessary condition and an expected outcome of the modeling process. In other words, the model is assumed to accurately describe its target, allowing its features to be related to those of the target. However, these features can only be fully defined and assessed after the model construction process has been completed.[8]

Second, the use of this kind of simulations as epistemic instruments[9] requires to enable the correspondence among semantically distinct domains, in a way that allows for different kinds of controlled misrepresentation (Pero & Suárez, 2016). This means that both representation and misrepresentation can coexist, once the main aim of the model is set towards a functional[10] or a structural representation. In other words, this accounts for modeling substructures that functionally represent the equivalent substructure in the target, without committing to strong isomorphism. For instance, the use of genetic algorithms to represent learning processes is not justified solely on the basis of their internal structures faithfully representing existing dynamics; rather, it is grounded in their capacity to approximate a dynamic of interest (see e.g. Chattoe, 1996). However, the trade-off between structural closeness and output efficiency significantly impacts model interpretability, as it is impossible to evaluate ABMs solely based on their output. In point of fact, this epistemic dilemma greatly affects the assessment of modeling, since the same modeling process is inherently iterative (Nersessian, 2002). By repeatedly adjusting the model as needed, it is in principle always possible to accommodate the calibration on empirical data. In this regard, the nearly limitless degrees of freedom in model development bind ABMs to be representational, while demanding such representations to be, if necessary, about instantiation of theories and conceptual objects. This distinguishes ABM from other simulation and data-driven techniques, where stronger, often theory-driven, modeling constraints facilitate easier comparisons among different models and their outputs in relation to their targets (see e.g. Seri et al., 2022).

These issues resonate at multiple levels within the philosophy of ABM, leading to a variety of approaches and proposed solutions that are rarely mutually exclusive. Instead of forming a strict taxonomy, they encompass different research dimensions (for a review of philosophical implications of ABM, see, for example, Anzola, 2021; Secchi, 2022). In point of fact, ABMs must have specific invariant properties that enable the transfer of knowledge to previously unknown domains (e.g. Alvarado, 2021; Humphreys, 2004). Strategies to investigate these invariant properties include:

- reducing epistemic activity to an already accepted model, such as the deductive-nomological method;
- demonstrating that epistemic operations are process-equivalent, by incorporating causality and/or explainability into the discourse;
- emphasizing how the model's structure or performance ensures stability in transferring meaning across domains.

Although these areas of research are interconnected, they are usually developed in different strands of literature. In the following, we will prioritize the third approach, focusing on the proper mapping between simulations, targets and theories tied to specific modeling purposes. This will lay the groundwork for exploring its main implications in other domains.

2.1.1. Four approaches

By looking at the way in which there is consistency in (or mapping of) the transfer of meaning between targets and simulations, four main approaches can be identified. It should be noted, however, that authors may employ hybrid approaches or ones that do not fit neatly into rigid categories. In the reminder of the subsection, we present an overview of these four approaches.

The Minimal Ontological Commitment Approach. This approach relies on consensus within the community to define the model's uses and applicability based on agreed-upon best practices.

The general aim of the minimal commitment to ontological positions is to intentionally avoid the intricacies typical of the philosophy of simulations (e.g. Dosi & Roventini, 2019). In such a context, the concept of virtual laboratories is often employed to provide narrative cohesion in specific model developments, by viewing ABMs as quasi-experiments and tools for constructing counterfactual scenarios in artificial societies (e.g. Anzola, 2021; Casini & Manzo, 2016). This strategy led to major advancement by suggesting rules for model construction regarding purposes (Edmonds et al., 2019; Edmonds & Meyer, 2017; Epstein, 2008; Grüne-Yanoff, 2013), and by developing quantitative methods for model calibration and validation (e.g. Grazzini et al., 2017; Guerini & Moneta, 2017; Lamperti, 2018; Ligmann-Zielinska et al., 2020; Platt, 2020; Seri et al., 2021).[11] The primary limitation of these approaches is that they offer practical insights without fully clarifying key elements within the chosen strategies (e.g. Ahrweiler et al., 2004; Gilbert & Ahrweiler, 2005; Gilbert et al., 2018). For instance, benchmark rules based on practitioners' experience do not offer any specific conditions for generalization, other than suggesting a possible (limited) application (e.g. Edmonds et al., 2019). Moreover, methodological and statistical suggestions remain largely unrelated to each other. While they may provide detailed application rules that heavily depend on available data for calibration and validation, they lack guidance on how to adjust the model (e.g. Grazzini et al., 2017; Guerini & Moneta, 2017; Lamperti, 2018; Ligmann-Zielinska et al., 2020; Platt, 2020; Seri et al., 2021). In general, assumption development, model design and their successive evaluation are left to the modeler's expertise.

The Generative-Deductive Approach. The idea behind this approach is that explanations in ABMs come from the structure of the model itself, which is derived axiomatically as a generating rule (e.g. Epstein, 2006). A refined deductive approach can be formulated within the inferential view, where simulation is framed as a broader argumentative tool that also fulfills an experimental function (Beisbart, 2012, 2018). This refined version aligns with the nomological-deductive method, as it involves the testing of specific hypotheses (Mauhe et al., 2023; Troost et al., 2023).

The Structural Similarity Approach. In this framework modelers assign a model to a target within a specific scope, justified by adequacy and two fidelity criteria: dynamical fidelity, that is output proximity to the phenomenon under investigation, and representational fidelity, which evaluates 'how well the structure of the model maps onto the target system of interest' (Weisberg, 2013, p. 41). Both criteria rely on a measure of 'closeness' (Weisberg, 2013). The consistency of the mapping process is achieved by ontologically restricting the model to mathematical models (Weisberg, 2013). This approach addresses the issues related to mapping consistency by emphasizing the need for context-based evaluation procedures. This can be achieved by defining a measure of similarity (Weisberg, 2013), by individuating homomorphisms among constituents based on relevance and similarity (Boge, 2020), or using similarity and analogy as ranking parameters within established empirical models (e.g. Casini, 2014; Manzo, 2022). In the first case, Boge (2020) accounts for homomorphic transfer from mathematical rules to the computational constituent, via discretized, computerized and compiled models. Notably, he explicitly refers to these transfers as analogical inferences based on formality and relevance across different systems. In the second case, Manzo (2022) justifies model selection primarily by appealing to a pluralist account of causality in ABM, which serves as a binding element with empirical soundness. This reinforces a claim to the structural nature of the

ABMs under scrutiny. In any case, the source of justification remains entirely on the empirical adequacy to the available data.

The Structural Representational Approach. Graebner (2018) integrates key elements of the Weisbergian ontology into a novel representational framework derived from the DEKI framework (Frigg & Nguyen, 2016). This framework, which is named after the four steps of the model, that are Denotation, Exemplification, Keying up and Imputation, endorses a fictionalist perspective describing the act of modeling as designing games of make-believe or narrations portraying targets, transitioning from model-specific features to those ascribed to targets (Frigg & Nguyen, 2016).

2.1.2. Limits and challenges of the four approaches

To assess the theoretical consistency of ABMs, an epistemic framework should explain how a representation may work both as a constructive principle and as a validated object. In point of fact, this would enable us to define the conditions for ensuring model *adequacy* and model *credibility*. We consider a model 'adequate' if its simulation and the relationships among constituents are meaningfully connected to the theoretical background and aligned with the chosen target, based on the modeling purpose (e.g. Parker, 2020), even in the absence of representation. A model is deemed 'credible' when it is considered adequate and its simulated output is regarded sufficiently close to the target output (see Gelfert, 2019). Therefore, the limits of the existing frameworks cannot be underestimated, as different approaches come out with different trade-offs. First, even if a minimal ontological commitment has proved to be successful in some contexts, the absence of a satisfactory framework for evaluating the appropriate mapping between theory, model and target undermine the validation of the theory. Second, the generative-deductive framework marginalizes the role of approximation and randomness. As a matter of fact, the deductive approach does not reflect the actual inferential content of ABM, in which outputs aggregate multiple model runs under known constraints and model correctness ensues from stability of runs within a predefined range. Moreover, even in its refined version, the validity of the premises in the argument, especially regarding model adequacy, can only be assumed. Thus, instead of describing the inherent inferential structure of ABMs, the scope of this framework lies in sketching out the potential use of the model under either specific requirements (Troost et al., 2023) or postulates (Mauhe et al., 2023). Third, the structural similarity approach faces several issues in delimiting the mapped object. In fact, in the Weisbergian construal framework, the adequacy of the model is found through tailored arguments, while the Boge (2020) model is too rigid to effectively explain highly idealized ABMs in social science, such as the Schelling model. In this case, rules may not truly align with actual agents in relevant ways (Boge, 2020), as no clear criteria for selecting variables are provided. As such, incorporating an extrinsic principle for empirical validation, for instance the resemblance between the target and the simulation, is unhelpful. In general, this approach overlooks the existence of multiple models that can explain the target (*equifinality*, see e.g. McCulloch et al., 2022) and the possibility of having several outputs arising from the same model (*multifinality*, see e.g. Valogianni & Padmanabhan, 2022). Lastly, the structural representational approach remains silent on the ontogenesis of the model. In particular, it fails to explain how the DEKI phases are implemented. Moreover, it outlines conditions that must be simultaneously met to evaluate a correct representation, even though the explanation unfolds in sequential phases. In addition, it is unclear how the denoted elements and internal relationships in the conceptual constituent justify the variable choices in the computational constituent, since the use of the DEKI account is limited to the mapping between the computational model and the target.

A further consideration may help us move in a different direction. In ABM, meaning arises from the cross-reference *within* and *among* the elements of the different constituents, such that the overall cognitive task of creating and sustaining meaning is inherently *distributed*. This bears several epistemic consequences. First, the modeler's interpretation of the constructed ABM is neither complete nor necessarily correct due to the complex decision-making process implicated in developing the different model constituents.[12] Second, knowledge generation processes must rely on the integration of model constituents, assumptions, empirical data, theoretical frameworks, benchmarks and epistemic communities from various, heterogeneous, sources (Giere, 2002; Magnani, 2017). Third, the epistemic value of such integration is bound by both the characteristics of the model and its intended use.[13] As a result, the epistemic justification for transferring meaning between a simulation and its target is obtained by decomposing the process into analyses of how meaning is conveyed within each modeling layer relative to the intended purpose. Thus, evaluating an ABM requires moving beyond a purely pragmatic target–model correspondence to include the target, the purpose, the theoretical background and the model's constituent layers as integral components of the assessment, thereby offering a theoretical justification for the previously normative definition of 'model adequacy.'

Furthermore, the assessment of the model's adequacy may occur during different phases, both when the modeler revises or changes parts of the model, and later, after the model's completion. Although this assessment happens in different contexts, and therefore retains different levels of epistemic strength, it involves similar operations. During the modeling phase it lies within the verification process, whereas after the model completion it is a form of validation.

The next section examines the internal structure of ABMs, with a focus on how meaning is transferred across constituents through specific inferential structures.

2.2. Model constituents and (their) inferential structures

Following the previous discussion, this section turns to the internal architecture of ABMs with the aim of clarifying how meaning is conveyed across their constituent layers. It introduces the three principal components of an agent-based model: the conceptual, algorithmic and computational constituents, as discussed in previous literature (e.g. Durán, 2020; Graebner, 2018), and examines the inferential structures that support their integration. The analysis shows how theoretical consistency relies on the coherence of these internal transitions, which underpin both model construction and epistemic function. Section 2.2.1 outlines each constituent. Section 2.2.2 then examines the inferential structures that mediate the transfer of meaning between them.

2.2.1. Computational, algorithmic and conceptual constituents

The *computational constituent* is the coding and the structure behind it. This is the result of programming activities that form the formal structure of a simulation model. It includes, for example, the use of databases, libraries and predefined functions (e.g. pseudo-random number generators) on a physical computer. This definition merges the notion of 'simulation model' in Durán (2020) and the ones of 'computerized' and 'compiled' model of Boge (2020). Two aspects are crucial here. First, the features of the computational component require an environment. And this should be appreciated in socio-technical terms since different scientific and technical communities offer different insights useful to guide modelers on the choice of programming language, computational templates and the correspondence between theories, data and the simulation model.

The *algorithmic constituent* involves the actual procedures and the rules that make outputs possible given the inputs. Since this element specifies the formal procedures and rules that are then translated into the computational constitutent through coding, the description of the algorithmic constituent may partially overlap with the conceptual constituent (Boge, 2020; Weisberg, 2013). This relates to the fact that algorithms are typically expressed in flowcharts and pseudo-code and they are partly subsumed within the programming language environment.

The *conceptual constituent* is generally specified by a comprehensive description, where formulations, model origin, intended scope and strategies are collected through annotations, that may take the form of scientific papers. Some scholars connect it directly to the formal structure of the model (e.g. Weisberg, 2013). The use of high-level languages for implementation complicates this characterization, since most languages allow to label variables directly within the code, making the ambivalence of some conceptual constituents more apparent. A tool to help modelers reflect on the intricacies of the conceptual constituent is the ODD protocol (Overview, Design, Detail; see e.g. Grimm et al., 2020). From this tool and the way in which concepts are typically defined, it is apparent that this constituent cannot be simply reduced to a block of axioms (Borgonovo et al., 2022; Giere, 2006). On the contrary, the conceptual structure is formed by an intertwined net of constitutive *building blocks* (Berger et al., 2024; Boero & Squazzoni, 2005), i.e. clearly identifiable portions of a model that, due to their characteristics, are involved in a generative process aimed at fulfilling some kind of abstract dynamic called *principle* (Borgonovo et al., 2022). It is worth noting that the definition of building blocks emphasizes their role as constitutive units of a process or mechanism, rather than specifying the exact nature of the mechanism they instantiate. Building blocks are therefore both modular and decomposable into their own components, which may also be building blocks. Conversely, principles are teleological in nature: they point to purpose-oriented, high-level elements, either embedded within the model's initial assumptions or anticipated as outcomes. Considered together, principles and building blocks offer a complete picture of the theoretical side of the model (Figure 1).

2.2.2. Inferential structures

The epistemic justification of ABMs depends on how meaning is transferred both internally, across the model's constituents, and externally, toward the target system the model aims to represent. Coherent inferential links are thus needed to ensure that meaning is appropriately conveyed across these layers, in order to explain (a) the relationships between the constituents described above and (b) the connection between the simulation output and its target. Of course, there are other types of mapping, for instance, the consistency between the empirical data and the internal workings of the model. In this paper, our claim is primarily focused on (a) and (b). That is, assumptions encoded at the conceptual level must be traceably transformed into algorithmic procedures and, in turn, into computational operations.[14] However, neither purely deductive inference nor a reliance on induction provide the necessary reliability and flexibility. On the one hand, deduction fails in the presence of digitization, approximation and idealization (e.g. Weisberg, 2013), since it is associated with a deterministic logic that is incapable of mapping the workings of CSs in general, and ABMs in particular. On the other hand, induction is a weak notion (Magnani, 2009). As previously pointed out, ABMs cannot be evaluated solely based on their outputs since the risk of overfitting or ad hoc adjustments is always present. Any form of explanation relying on an inductive iteration requires an external semantic justification, e.g. in the form of an assumption concerning a mechanism or a regularity. This is true also when relying on a probabilistic notion of causality (e.g. Granger, 1980; Mosconi & Seri, 2006).[15]

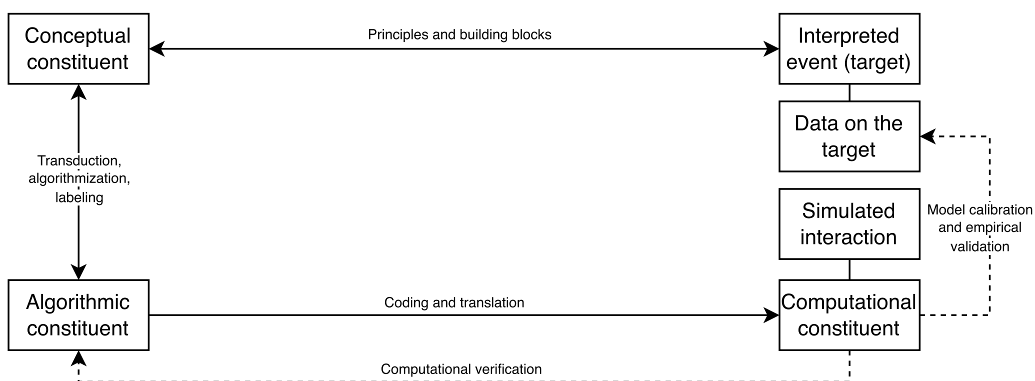

Figure 1. The relationships between conceptual, algorithmic and computational constituents.

A third form of inference, abduction, seems *prima facie* a better candidate as it allows for making inferences to the best explanation (e.g. Douven, 2021; Magnani, 2009) or for generating new hypotheses (e.g. Douven, 2021; Magnani, 2009). We consider abduction as formally entailing a propositive 'affirming the consequent' fallacy (Magnani, 2009) and, for that reason, we exclude from the present consideration what Thagard (1988) defines as analogical abductions, which entail the use of analogies for abductive purposes. Thus, abduction can be either *theoretical*, i.e. deriving from existent models, or *manipulative*, which applies actual changes to the target involved (Magnani, 2009). Moreover, it sustains inferences in different-domain contexts. However, it has some limitations. First, it is not transitive (Magnani, 2009). Second, although the entire process of justifying a simulation can be viewed as abductive reasoning, the internal justifications within the model are not inherently abductive. Therefore, it is not apt for being used as an inference under letter (a) above. For instance, the choice of a specific computational template may appear justified by existing literature on previous results. Yet, the outcomes from applying this template to the current case are not warranted by past applications, thus limiting its use as a form of abductive analogy (e.g. Boge, 2020; Thagard, 1988). As such, abduction plays a fundamental role in the actor-model interaction, but does not explain either the construction process, or the relations within the model.

2.3. On analogy and ABM

Another form of inferential argumentation is analogical inference. This form appears to be tackling with representation at a different level than induction, deduction and abduction because it is not specified by formal logic to the extent those three forms are. Indeed, CSs have explicitly been considered as analogies with respect to three aspects: the mapping over different substrata as computing digital machines (Boge, 2020; Symons, 2008b; von Neumann & Kurzweil, 2012), their internal formal structure (Bunge, 1973)[16] and their heuristic power (e.g. Edmonds et al., 2019; Hartmann, 1996). Therefore, it appears to be at least appropriate to use the notion of analogy as a perspective to address the challenges discussed above. The remainder of this section clarifies how analogical inference can be systematically unpacked and evaluated in the context of ABM.

2.3.1. Analogical inference and conceptualization

An *analogy* is a comparison relying on some kind of extensional or intensional similarity (Melandri, 2004) between at least two objects (e.g. Bartha, 2022), properties (e.g. Juthe, 2005), relationships among properties (e.g. Bartha, 2022; Juthe, 2005; Melandri, 2004) and operations among properties (e.g. Alvargonzález, 2020; Simondon & Adkins, 2020). This form of comparison allows for highly complex and flexible considerations. First, analogies are fruitful not only for same-domain but also for different-domain inferences (e.g. Bartha, 2022; Boge, 2020; Juthe, 2005). Second, analogies can be *positive*, indicating an accepted correspondence with a similar relationship, *negative* if the correspondence is invalid, or *neutral* if the status of correspondence within the target is unknown. Consequently, they may hold despite some distortions in representation (Hesse, 1966). Third, analogies can be transitive (Bunge, 1973). Lastly, analogies are implied whenever a logical determination is not possible and either a shift is required between particular contents or forms (*inferential*), or a generalization and a novel interpretation is required (*conceptual*) (Melandri, 2004).

The contemporary analytical study of analogy has spanned logic (e.g. Barbot et al., 2019; Holyoak et al., 2010; Juthe, 2005; Pietsch, 2019; Schoonen, 2022), philosophy of science (e.g. Bunge, 1973; Guala, 2010; Hesse, 1966; Melandri, 2004; Nersessian, 2008), cognitive (e.g. Gentner, 1983; Gentner & Hoyos, 2017) and computational (e.g. Holyoak et al., 2010; Holyoak & Thagard, 1995) traditions. Here, we primarily reference Bartha's articulation model (2010) due to its preeminence and generality in the examination of scientific analogies.

From a formal standpoint, an analogy is constituted by projecting an element of a source (or Analogue) onto an element of a Target-Subject. Therefore, its strength is defined by its internal structure. First, the deeper the relations among the known similarities within the source and the element that must be projected on the target, the stronger the relation is likely to be. These *vertical* relations, i.e. those interconnected internal characteristics of the Analogue that one is willing to map, ensure *prior association*. Then, *horizontal* correspondence, called *potential for generalization*, unifies the source and domain by the presence of an element of the target within the positive analogy *(overlap)*, and the absence of a defeating condition in the analogy *(no-critical-difference)*. Moreover, analogical inference encompasses various modes of association, whose range encompass, among others, (a) *predictive,* (b) *explanatory,* (c) *functional* or (d) *correlative* inferential structures (Bartha, 2010). Here, conditions of an analogy are explored based on these modes of association and the form of similarity involved (Bartha, 2010). This overall depiction raises two concerns in the context of ABM (Figure 2).

First, the Barthian framework is designed to provide the foundations for a theory of *individual* scientific analogy. As such, its scope is limited to simple analogies as it may be practically challenging to interpret and handle multiple and nested analogies.[17] However, while this condition is the most tractable, in the present context of ABM it is also necessary to ensure that an analogical framework can accommodate nested analogies. In this respect, Bunge's (1973) treatment of simulation provides a pertinent precedent. In fact, he posits two constraints for any simulation: first, the simulated object must be *contagiously* analogous to its target, that is related by a transitive analogical relation, and second, the analogy must possess significance, whether intrinsic or conferred by a third party. Accordingly, a simulation can be regarded as supported by multiple, potentially nested, analogies. Nevertheless, to avoid circularity or other inconsistencies, we may constrain nested analogies to be valid only if, at each level of abstraction (LoA) (e.g. Floridi, 2008, 2011; Symons, 2008a), at least one element of the analogue corresponds to an element of the target. This solution further affords the advantage of accommodating different kinds of morphisms according to context and level of analysis.

A second point concerns the evaluation of analogies. Criteria are contextually embedded in the field of analysis and the interplay between vertical and horizontal relations.

In order to address these two critical points, a pragmatic evaluation of each analysis is required. This must embrace:

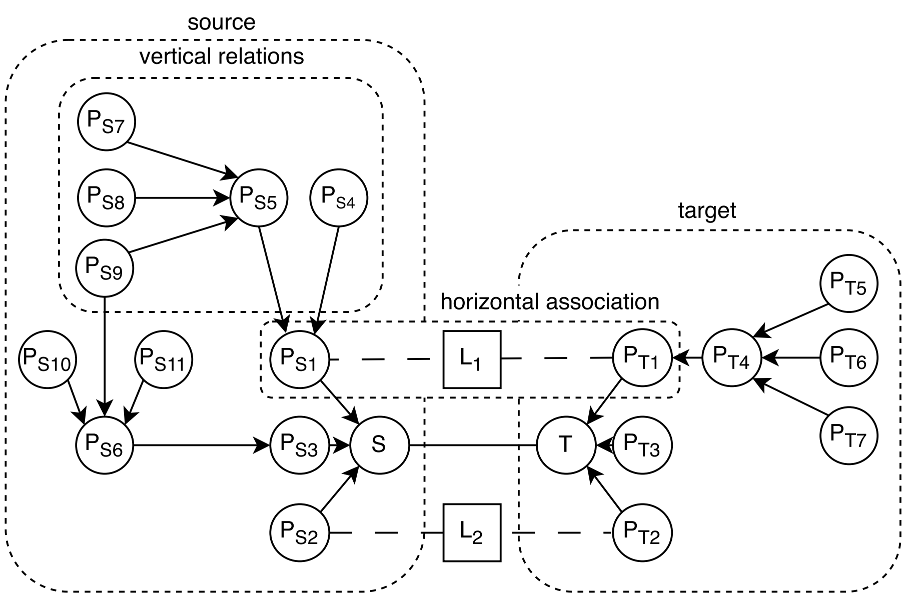

Figure 2. The structure of an analogical inference where the source S maps a property P_{S1} onto a similar property P_{T1} of the target T by association L_1. As it can be seen, P_{S1} is bound within the source by the vertical relations $P_{S4}, \ldots, P_{S5}$ composed by $P_{S7}, \ldots, P_{S9}$.

- the context of the analogy;
- the explicit or implicit purpose behind the analogy formulation;
- the structure of the analysis concerning both context and purpose.

Hence, analogy evaluation involves a dual *a posteriori* analysis. The first one is related to conditions derived from the specific field where the analogical argument is constructed. The second one concerns the instantiated argument and its purpose. This approach is not unique. Regardless of the theoretical point of departure, assessing inferential robustness in analogical reasoning requires to identify a set of *anchors* within a specific analogy form and discipline, pragmatically identified with clear structural meaning. Differences among the structure-mapping theory (e.g. Gentner, 1983; Gentner & Hoyos, 2017), the multi-constraint theory (e.g. Bartha, 2010; Holyoak & Thagard, 1995), the case-based reasoning (e.g. Bartha, 2010) and the probabilistic-analogical framework (e.g. Holyoak et al., 2010) can be found in the updating mechanism underlining this search. Bartha (2010) outlines a three-stage process to ensure analogy robustness:

(1) Elaboration of prior association by considering the category of the analogy and the preconditions of the prior association: prioritizing vertical ties is crucial, as the analogy's strength is constrained by its source argument.
(2) Determination of relevance of horizontal ties: further elaboration of prior association may be necessary at this stage.
(3) Assessment of potential for generalization, in order to connect source and target.

2.3.2. Analogy and ABM (What does it mean for ABMs to be constituted by analogies)

The concept of analogical inference preserves the epistemic value of modeling since it enables structural decomposition and interpretation of semantic transfer within different model constituents. As such, this provides us both with a structural interpretation of the transfer of meaning among the different constituents and with a method to investigate model adequacy. Units of analysis and primary units of analogical mediation are here the building blocks. Each building block embodies a specific portion of the model's theoretical content and serves as a locus where inferential links can be established across layers. That is it acts as an 'anchor' through which conceptual assumptions are transduced into algorithmic logic and encoded in computational form. Treating building blocks analogically means that each must support both vertical coherence (within the conceptual layer) and horizontal relevance (toward the target domain), while also maintaining inferential continuity with its algorithmic and computational counterparts. As such, model adequacy decomposes into three parts: (a) conceptual constituent adequacy to the target, (b) conceptual constituent adequacy to the algorithmic constituent, and (c) algorithmic constituent adequacy to the computational constituent. These three phases mirror the structure offered by Bartha's (2010) articulation model. For example, the adequacy of a conceptual constituent to a target is determined by:

(1) The coherence of the conceptual constituent according to state-of-the-art research and the relative embeddedness of its building blocks in the overall conceptual model.
(2) The presence of strong horizontal links between the conceptual constituent and the known interpretation of the target through state-of-the-art research and known empirical regularities of interest, for the majority of relevant properties not directly under investigation, i.e. the *neighboring properties*.
(3) The absence of *defeating conditions*, that is negative analogies within the core of the constituent concerning the target which directly affect the interpretability of their neighboring properties.

The coherence of a conceptual constituent, that is its vertical associations, is assured through the internal coherence of its parts, i.e. the building blocks, and the overall principles governing their combination.

Similarly, the adequacy of the conceptual constituent to the algorithmic constituent is determined by:

(1) The formal consistency in the internal relations of the algorithmic constituent.
(2) The presence of strong horizontal links between the conceptual and the algorithmic constituents for any of the mapped properties.
(3) The absence of processes outside the scope of the conceptual constituent.

These conditions are guaranteed through conceptual *transduction*,[18] *algorithmization* and variable assignment, hereafter referred to as *labeling*. Conceptual transduction and algorithmization involve creating and selecting computational templates, while labeling semantically denotes the formulation, ensuring adherence to the conceptual constituent. The correctness of the assignment depends on whether the behavior of a given agent or a collective of agents within the conceptual constituent reflects the formalization. Furthermore, the adequacy of the algorithmic constituent to the computational constituent progresses through translation and encoding. This phase is subject to conditions akin to those stated above, as the translation phase involves finding a compromise on the programming language ecosystem.

As such, model adequacy is not *a priori* assured, but can be assessed. In fact, each building block represents a coherent portion of the conceptual model, grounded in a theoretical principle, and functions as a bridge across model layers, enabling analogical transfer from conceptual assumptions to algorithmic logic and computational implementation. This layered connectivity requires each block to exhibit internal coherence, resemblance to the chosen target and implementation traceability. In this context, *abstraction* and *composition* play a fundamental role in the epistemic reconstruction of the model. Abstraction refers to the process of isolating the underlying theoretical assumptions embedded within a building block, especially when they are not explicitly stated but instead encoded in algorithmic or computational structures. Composition, on the other hand, refers to the integration of these blocks into a coherent explanatory architecture, allowing one to assess whether the set of assumptions forms a structured and interpretable whole. Together, these operations contribute to clarifying both the internal coherence of individual components and their systemic alignment across modeling layers.

Here, such assessment can take two different forms: during the modeling construction as a form of theoretical verification, and once the model is deemed finished as theoretical validation. While the former comes at the very heart of the modeler's activity, and often resolves itself in evaluating several modeling possibilities by engaging with accustomed best practices within the epistemic community of reference, the latter has not received so far enough attention. Potentially, we can distinguish between *model reconstruction* and *conceptual reconstruction*. *Model reconstruction*, simply stated, implies the replication of the entire ABM under scrutiny, whereas *conceptual reconstruction* evaluates the correspondence between theory, target, the conceptual constituent and the algorithmic constituent. Here, conceptual reconstruction plays a key role: on the one hand, it is a necessary phase in model reconstruction; on the other hand, it fulfills the need of a method for evaluating the theoretical consistency of an ABM. Two strategies can be applied to achieve this goal. The first one entails the *systematic* conceptual reconstruction of the conceptual constituent according to the three phases formerly described (Figure 3).

The second strategy defines a *minimal* reconstruction, that is focused on searching for contextual negative analogies vis-a-vis the target of the model to screen if there are plain defeating conditions. Indeed, abstractions and idealizations are essential in modeling but require justified analyses of their impact on the model based on state-of-the-art research. Such a minimal reconstruction allows for a rapid search for the conceptual weaknesses of the model.

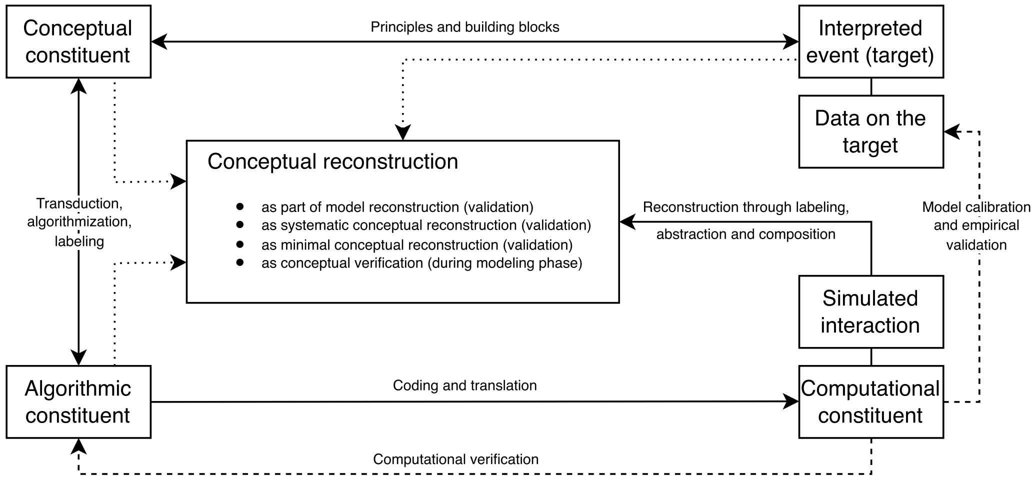

Figure 3. Conceptual reconstruction as mediator tool to evaluate the simulated interaction in relation to constituents assumptions and idealizations.

Lastly, the analogical conception of ABM crucially contributes to model interpretation and evaluation of model credibility. Different purposes entail distinct inferential uses of analogy and necessitate to focus on either the algorithm's structure or output. The next section illustrates a case study of a minimal conceptual reconstruction in the economics of innovation field.

2.3.3. Operationalizing conceptual reconstruction

Building on the three inferential mappings, we focus here on the conceptual constituent of an existing ABM, providing an evaluation roadmap for conceptual building blocks and principles divided in four stages. The roadmap is valuable for both systematic and minimal conceptual reconstructions.

Block identification and principle alignment. First, discrete conceptual building blocks should be identified. This result is reached by looking at the modular components embodying a specific motivating design principle. Since building blocks are compound structures, these can be further inspected in their constitutive items. Each discrete conceptual block (e.g. 'network formation' or 'innovation hypothesis') is extracted from the model text, and its motivating design principle (e.g. heterogeneous collaboration or endogenous innovation) is recorded. These blocks are typically reconstructable from the model documentation or theoretical background and correspond to coherent assumptions that play a distinct role in the model's conceptual logic.

Conceptual → Target adequacy. Each block is evaluated for internal coherence with respect to state-of-the-art theory and assessed for its embeddedness in the overall conceptual model. The presence of horizontal links to established interpretations of the target is verified, and it is ensured that no defeating conditions compromise its adequacy to the target under investigation. In accordance to the previous definition, a defeating condition entails any assumption, abstraction, or simplification that, once made explicit, undermines the intended correspondence between the block and the target system. For instance, assuming fixed agent behavior in a context that requires adaptive learning, or excluding institutions from a model of institutional innovation, would constitute a defeating condition.

Conceptual → Algorithmic mapping. Published rules or flowcharts are examined to confirm that each conceptual element is represented by a corresponding formal component. It is verified that variable names and procedures reflect the original conceptual content transparently, and that no extraneous processes have been introduced. The mapping is considered successful when the implemented logic preserves the structure and intent of the original assumption.

Conceptual → Computational tracing. Finally, we verify that each concept appears as a self-standing construct in the code, class, function or module, whose interface and attributes directly mirror the intended conceptual entity. This includes checking whether the code implementation preserves semantic continuity with the conceptual structure, and whether the block can be traced across layers without distortion.

The outcomes populate a *conceptual reconstruction matrix*, with rows for conceptual blocks and columns for each of the four stages. This matrix makes explicit the analogical commitments of the model's theory, highlights any critical mismatches, and provides a clear blueprint for subsequent algorithmic validation and code review. Cells are populated with brief qualitative assessments (e.g. 'adequate,' 'partial,' 'missing') or explanatory remarks, allowing for targeted diagnosis and revision.

3. ABM in the economics of innovation field

Innovation arises endogenously within economic systems, displaying non-linear emergent patterns from interactions among heterogeneous actors (see e.g. Hall & Rosenberg, 2010). As such, it has been extensively investigated via ABM, making it an ideal case to explore the analogical roots of economic ABM. This section evaluates two influential ABMs in the economics of innovation field, namely the Simulating Knowledge dynamics in Innovation Networks (SKIN) by Ahrweiler et al. (2004), Ahrweiler

Table 1. Core building blocks, principles, characteristics & limits of original SKIN model.

Building Block	Implementation	Underlying Principle	Characteristics and limits
Agent	Firms instantiated with kene triplets (each framed with capability, ability and expertise) and capital stock.	Heterogeneous agents	Differentiates firms by knowledge endowment; omits consumer/household heterogeneity and all institutional variation.
Knowledge engine	Genetic search: ±1 ability mutations each turn; capability × ability determines technology; ability × expertise determines quality.	Endogenous innovation	Redefines innovation intensity based on past failures; captures incremental and radical R&D but excludes path-dependent lock-in, external knowledge sources and institutional R&D incentives.
Partner matching	Innovation-hypothesis adverts under conservative vs. progressive rules to form networks.	Heterogeneous collaboration	Models both homophily and heterophily yet abstracts from non-market partner selection (grants, regulation) and search costs beyond matching algorithm.
Network agent	Network entities inherit parent firms' kenes; share profits; formation costs applied; one network per firm.	Firm autonomy	Pools knowledge within networks; ignores multi-network participation, governance, institutional oversight and associated transaction costs.
Start-up clone	Emergence of inexperienced mimetic clones in profitable sectors, constrained by tacit knowledge.	Mimetic entry	Captures imitative entry; omits non-imitative entrepreneurship, policy-driven entry incentives and diverse founding strategies.
Market structure	Closed B2B market with exogenous, price-capped demand; no taxation or quality competition.	Closed-market equilibrium	Enforces fixed, capped demand; omits taxation, quality-based competition, demand shocks and any price-diversification strategies.
Institutional layer	Absent–no institutional actors or regulations are modeled.	Institutional abstraction	Omits all institutional actors and policy mechanisms; excludes taxation, subsidies, regulation and their effects on innovation dynamics.
Financial flows	Firms earn revenue from sales and pay R&D costs; no credit or subsidy mechanisms.	Profit-driven dynamics	Models only basic revenue-cost flows; excludes financial markets, borrowing, savings, subsidies and any fiscal policy interventions.

Table 2. Core building blocks, principles, characteristics & limits of original K+S model.

Building Block	Implementation	Underlying Principle	Characteristics and limits
Agents & sectors	Machine producers; consumption-goods producers; labor; government (taxation & redistribution).	Multi-sector heterogeneity	Represents production, consumption, labor and government roles; omits households, financial intermediaries and non-governmental institutions.
Innovation engine	Two-step Bernoulli draw for technological 'access' for each period; fixed split of R&D between innovation and imitation.	Endogenous technological change	Captures R&D uncertainty and efficiency gains; excludes radical breakthroughs, product diversification and dynamic R&D intensity adjustments.
Production cycle	Sequence: machine firms advertise efficiency gains $\rightarrow$ consumption firms decide output, investment, suppliers $\rightarrow$ hiring $\rightarrow$ production.	Sequential inter-sector feedback	Captures value-chain interactions; omits quality competition and network effects.
Market module	Imperfect competition for consumption goods; market shares evolve on price competitiveness; exit/entry maintains constant firm count.	Price-driven market selection	Accurately models price competition and turnover; abstracts from non-price factors such as brand, quality, network externalities and demand shocks.
Network agent	Absent – no explicit inter-firm or knowledge-exchange networks are modeled.	No networked collaborations	Omits all forms of collaborative networks, alliances or knowledge spillovers beyond market transactions.
New entrants and population scale	Exit on low share/negative assets; spawn naive entrants.	Constant firm population	Maintains a fixed number of firms; omits endogenously driven entry diversity, firm heterogeneity among entrants and policy-driven churn or barriers to entry.
Institutional layer	Government actor sets tax rate, conducts redistribution, but no other regulatory or institutional bodies; policy is exogenous and fixed over time.	Governance abstraction	Includes simple tax-redistribution loop; omits regulatory bodies, policy endogeneity, public R&D funding and dynamic institutional change.
Financial flows	Wages paid to labor; taxes collected by government; redistribution to households; investment in new capital arrives with a one-period lag.	Macro-closure via fiscal & capital	Models essential fiscal flows and capital accumulation delay; excludes credit markets and broader financial dynamics that shape investment and innovation.

et al. (2011), and Gilbert et al. (2014) and the Schumpeter Meeting Keynes Model (K+S) (e.g. Dosi et al., 2013, 2010; Dosi, Napoletano, et al., 2017; Dosi, Pereira, et al., 2017; Dosi et al., 2018; Dosi & Roventini, 2019; Lamperti et al., 2018). The emphasis is directed towards elucidating the foundational components, that are the building blocks, of the 'innovating engine' of the models, in relation to their overall principles. Tables 1 and 2 summarize the main results. In doing so, we refer to the Schumpeterian, the evolutionary and the innovation system literature (e.g. Hall & Rosenberg, 2010; Lundvall, 2012; Nelson et al., 2018).

3.1. The simulating knowledge dynamics in innovation networks model

The SKIN model (Ahrweiler et al., 2004) is tailored to emulate knowledge-intensive industries with an internal business-to-business (B2B) market. It portrays firms as agents endowed with 'kenes' (see Appendix), constituent units of triplets of knowledge giving an abstract numerical representation of industrial *capability*, technological *ability* and firm *expertise*. Kenes determine the creation of new products, their characteristics and quality, which are defined from the multiplicative interactions of *capability* × *ability* and *ability* × *expertise*. Kenes evolve by employing a genetic algorithm with a limited random component, which is primarily implemented as dichotomous choices (Ahrweiler et al., 2004).

The foundational principles guiding the SKIN model encompass a closed market with interacting agents, collaboration among firms, endogenous dynamics of product generation and a genetic engine replicating knowledge production. These are mirrored in building blocks including the knowledge set defined by the kenes, different modes of innovation (incremental vs. radical), network creation and a selling market (Ahrweiler et al., 2004). Firms articulate an innovation hypothesis under either a conservative, like-capability strategy or a progressive, cross-capability strategy and advertise it. Successful advertisements enable the firm to produce and sell its product, which may be an intermediate one for the production of final products. Repeated failure at incremental search triggers costlier radical search. Profitable sectors spawn start-up clones, 'inexperienced' imitators constrained by tacit knowledge. Transactions occur in a closed B2B market characterized by exogenous, price-capped demand; taxation, quality competition and institutional actors are explicitly abstracted away. Moreover, the model allows for the establishment of network agents that inherit parent kenes, share profits net of formation costs, and abide by a one-network-per-firm limit.

3.2. The Schumpeter meeting Keynes model

The original K+S model outlines endogenous growth and business cycles within a closed-market structure featuring interacting agents in a two-sector economy (Dosi et al., 2010). The model's building blocks encompass a machine-production sector with stochastic innovation, a goods-producing sector, a labor sector and a government sector tasked with tax collection and redistribution (Dosi et al., 2010).

These sectors interact through sequential stages. First, machine-producing firms conduct R&D to increase the efficiency of their product and imitate competitors. Then, they advertise to consumption-good producers, which define production level and investments, select suppliers and place orders. Afterwards, both sectors hire workers and start production. An imperfectly competitive consumption-good market opens, with evolving market shares based on price competitiveness, and the government collects taxes on wages and profits. Entry and exit processes occur, removing firms with near-zero market shares and negative net assets and replacing them with new entrants. Lastly, machines ordered by capital-good firms at time t are delivered in $t+1$, becoming part of the capital stock (Dosi et al., 2010).

3.3. Assessing the conceptual constituent: elements of a conceptual reconstruction of innovation in the SKIN and K+S models

Applying the first two reconstruction stages, we identify and align each model's core blocks with their guiding principles and define their limitations with respect to their target. Results are summarized in Tables 1 and 2. The innovating engine of the SKIN model portrays the knowledge sphere as the primary catalyst of economic activity, subject to extensive abstractions and idealizations. Institutional drivers are absent, the artificial economy is balanced through exogenous, price-capped final demand, taxation is omitted, and costs are confined to purchases of intermediate goods or innovation activities (Ahrweiler et al., 2004). In the building blocks of the innovating engine, innovation efforts are redefined over time based on past failures, yet incremental and radical innovations do not generate path dependencies, and technological lock-in is effectively excluded. Moreover, competition primarily revolves around price rather than quality, that is without engaging in market diversification. These choices constrain the model's adequacy to specific targets and necessitate careful alignment between model assumptions and purpose. As a theoretical tool, SKIN explores the effects of network formation in knowledge production, maintaining a stable innovating engine across different network configurations. Nevertheless, causal analysis remains restricted by the exclusion of key exogenous factors. The model can also be informed with empirical inputs. In such cases, utilizing historical time series becomes crucial to understand network formation since the abstract innovating engine may not align with the actual firms' innovation process. An alternative approach involves exploring other types of knowledge-generating systems, such as scientific ones, for which the knowledge engine better resembles the innovating mechanism. However, even in that case the model must be tailored with case-specific assumptions, for instance by accommodating competition based on quality and opportunity-related R&D.

In the original K+S model two fundamental principles stand out. First, the model rejects the notion of a representative agent as inconsistent with economic reality, and motivates in this way the choice of an ABM. Second, the number of firms is kept constant by replacing dead firms with new entrants. This choice is consistent within the building blocks. For instance, innovation access is modeled as a Bernoulli distribution, which is consistent with Nelson and Winter (2004). Where explicit assumptions are absent, idealizations are carefully explained, such as the uniform R&D propensity across firms. Other abstractions are implicit. Innovation strictly enhances efficiency, without product diversification or radical breakthroughs, and R&D effort is divided in fixed proportions between innovation and imitation. These abstractions and idealizations constrain the potential adequacy of the model to a specific subset of targets. As a theoretical tool, the model tries to provide descriptive and causal explanations rooted in advancing economic theory. The descriptive function stems from the careful choice of building blocks. However, causal inference requires parameter calibration and empirical validation, which are complicated by the model's simplifying assumptions. In particular, the constancy of firm numbers and the exclusion of radical innovation constrain the model's ability to provide robust counterfactual predictions for policy analysis.

The examination of the SKIN and K+S models reveals context-specific risks and limitations. Both models incorporate idealizations that constrain their adequacy to specific subsets of targets and purposes. On the one hand, the SKIN model is constrained by idealizations embedded in its kene genetic engine and in the treatment of incremental and radical innovation. Risks stem from the adequacy of search and mapping functions, emphasizing the importance of carefully contextualizing the model's assumptions. On the other hand, the K+S model encounters challenges related to innovation mechanisms and system stabilization, raising the risk of over-interpreting model behavior and highlighting the need for caution when transitioning from theoretical description to causal inference.

Subsequent developments have aimed to address these challenges. In the SKIN family, a sociological strand has modeled non-market knowledge production networks with exogenous selection processes, such as in the NEMO-SKIN application to EU proposal systems (e.g. Gilbert et al., 2014), while innovation network research has incorporated hybrid stochastic mechanisms (e.g. Pyka et al., 2019). The K+S lineage has enhanced its modular structure, introducing greater model complexity, variable R&D intensities, endogenous entry and exit, and improved empirical calibration methods focused on causal validation (e.g. Dosi et al., 2023; Dosi, Napoletano, et al., 2017; Dosi et al., 2019; Lamperti et al., 2018).

4. Conclusion

In this paper, we first reviewed existing ontological frameworks for ABMs and then advanced a structural-analogical account by conceiving ABM as a multi-layered modeling practice in which meaning is distributed across conceptual, algorithmic, and computational constituents. The identification of a common inferential framework was necessary to understand how the semantic shift across the different substrata would not jeopardize the heuristic and synthetic use of ABMs. We excluded deduction, induction and abduction, concentrating our analysis on analogy, specifically by employing Bartha's articulation model (Bartha, 2010). Using this perspective, we introduced a pragmatic framework for evaluating analogical mappings across theory, conceptual constituents, purpose and target. Within this framework, we defined model adequacy as the condition whereby the simulation and the relationships among its constituents are meaningfully connected to the theoretical background and aligned with the chosen target, based on the modeling purpose, even when strict representational mapping is absent. We further defined model credibility as requiring a twofold condition: a model must first be adequate, and then its simulated output must be evaluated as sufficiently close to the expected behavior of the target system. Credibility thus involves a distinct, additional evaluation beyond internal coherence, tying the model's external performance to its theoretical structure.

Additionally, we introduced conceptual reconstruction as a method for assessing the internal consistency of an ABM by tracing building blocks and principles back to their conceptual and theoretical assumptions. Conceptual reconstruction proceeds through three stages: identifying contextual negative analogies, assessing them against the current literature and judging their justification according to the intended modeling purpose.

With this minimal reconstructive framework in place, we applied it to the conceptual constituents of two prominent families of models in the economics of innovation: the original SKIN (Ahrweiler et al., 2004) and K+S (Dosi et al., 2010) models. By following fundamentally different approaches in terms of target realism and modeling strategies, the models experienced different epistemic challenges and appeared inherently suitable for different modeling purposes. The SKIN model offers a theoretical and illustrative exploration of network effects and limited causality is supported in case of empirical calibration. In contrast, the K+S model sustains a theoretical descriptive analysis, and causality is granted through its direct and granular confrontation with economic theory. However, the potential to extend causality assessment as an empirically validated counterfactual is constrained.

These findings highlight that modeling constraints can be systematically interpreted as analogical constraints, and that conceptual reconstruction provides an effective tool for revealing them and proposing targeted improvements. Moreover, the historical evolution of both model families reflects a gradual response to the epistemic risks identified through this approach. Nevertheless, our study encounters limitations, which open up the space for further investigations. Firstly, the theoretical framework requires further elaboration, specifically in delineating the notion of causality supported by different models and the circumstances in which such notions are applicable. The diversity of causality claims in economics (Maziarz, 2020) necessitates a detailed understanding within the internal reference system of ABMs, and a structural-analogical account could contribute to this. For instance, our approach may exclude certain notions of causality, like the deductive-nomological framework. In addition, a more in-depth exploration of model adequacy and model credibility is essential, as they significantly impact modeling strategy. Lastly, the practice of conceptual reconstruction should be developed into an established methodology.

Notes

1. In the following, we refer to Agent-Based Modeling (ABM) as the process or methodology, whereas Agent-Based Models (ABMs) denote the constructed objects.
2. As recently pointed out in a comprehensive theoretical review by Pero (2024), the notion of target is multifaceted and has a direct impact on modeling activity. More precisely, targets are understood as the ultimate object of analysis emerging from a partitioning of phenomena or structures, that are otherwise too complex to be analyzed. As such, they bear interesting properties. For instance, they are often co-constructed in relation to the model and allow for type-token distinctions (Pero, 2024). Consequently, a proper analysis of a target can be only situated in connection with the model and the modeler purpose. For what concerns a general taxonomy, we follow the existing literature (e.g. Boero & Squazzoni, 2005; Weisberg, 2013) that distinguishes between *specific*, denoting an individual phenomenon, *generalized*, encompassing a class of phenomena, or *non-existent*, including conditions in which neither an individual instance of a phenomenon nor a class of phenomena can be denoted. By empirically grounded targets we indicate targets for which an individual or a class of phenomena are clearly identifiable *and* it is possible to have access to external data from the phenomenon, or the class of phenomena, at hand.
3. For clarity, we will use in the following the terms constituents and constituent layers to denote the model components instantiated across different semiotic systems. See Section 2.2 for a description of the constituents.
4. This transfer is supported by the fact that ABMs are usually implemented on computational devices and therefore are widely recognized as a specific subset of CSs (Humphreys, 2004). Moreover, CSs have been portrayed as instances of dynamic models with distinct temporal features (Hartmann, 1996). Transfer from CSs and theory-of-model literature in general to ABM in particular are made explicit along the text.

5. This conforms to models and scientific representation in general, especially in the *agent-based* (actor-based) perspective of Giere (2010).
6. These latter are not marginal, as ABMs result in a concatenation of different layers, which are instantiated on different structures. For a general review of the concept in CS literature see e.g. Boge (2020) and Durán (2020). In the context of ABM see e.g. Graebner (2018).
7. This conforms to the fact that models and CSs in general are both purpose-driven in relation to a target (Edmonds et al., 2019; Knuuttila, 2021a), which may be theoretical, idealized, generalized or actual empirical constructs (Magnani, 2009; Morrison, 2015; Weisberg, 2013), and their creation is shaped by the overall epistemic landscape of reference (Aydinonat et al., 2021; Bokulich, 2014). Modeling purposes also engage with the available external data, which are widely recognized as being non-neutral (e.g. Bokulich & Parker, 2021; Woodward, 2000, 2010), thus shaping the level of target accessibility.
8. This consideration is true for any technical object and, more generally, for any generated entity. As a philosophical issue, this can be considered in its static nature as the dyadic identification and relation problem (for an example regarding the theory of models see e.g. Salis et al., 2020) or in its dynamic nature as the problem of technical individuation (e.g. Simondon, 2011; Simondon & Adkins, 2020).
9. CSs in general have been widely regarded as epistemic instruments expanding the cognitive capacities of the modeler (e.g. Alvarado, 2021; Humphreys, 2004).
10. A theoretical example of purely functional representation is the prediction offered by a mechanical oracle (see e.g. Symons & Alvarado, 2019). The oracle represents in t the state of an object at $t + 1$, by employing mechanisms that are by definition different from the original ones.
11. We maintain the following distinction between verification, calibration and validation, although we acknowledge that several authors might adopt a different taxonomy (see e.g. Seri et al., 2021, p. 63). Verification assesses that the CS accurately specifies desired numerical conditions and patterns. Following Durán (2013), three main verification activities are distinguished: (a) code verification, (b) calculation verification, (c) robustness analysis. Validation, on the other side, is a method for evaluating the CS by comparing results with data from other sources (Durán, 2013) and encompasses three distinct phases of input validation, process validation and output validation (e.g. Graebner, 2018). Regarding calibration, we refer to it as adjusting or tuning the model on existing data (e.g. Beisbart & Saam, 2019).
12. This adds up with the already known essential epistemic opacity that is due to the incapability, by the modeler, to inspect the actual computational processes of the simulations (see e.g. Humphreys, 2004).
13. Several research programmes have addressed this issue in their respective domains. Beyond the works cited in footnote 7 and the study of Nersessian (2022) about computational modeling in research teams, economists and social scientists have emphasized it by distinguishing epistemic requirements according to modeling purposes and strategies (Edmonds et al., 2019; Vriend, 2006).
14. The account developed here focuses not on external validation but on the internal referential structure that governs interactions among constituents. This perspective aligns with positions such as Weisberg (2013), which emphasize the importance of internal coherence in establishing theoretical consistency. At the same time, it accommodates a pluralistic view of modeling purposes: as emphasized in the ABM literature (e.g. Edmonds et al., 2019), different purposes may shape how a simulation is constructed and interpreted, and thus how meaning is distributed across its constituent layers. In this respect, we refrain from taking a stance on the longstanding philosophical debate about the kinds of inferences simulations may support – whether they are best conceived as experimental tools that extend epistemic access (e.g. Boge, 2019; Morgan, 2004; Parker, 2009), or as argumentative constructs embedded in broader justificatory practices (e.g. Beisbart, 2012, 2018; Beisbart & Norton, 2012). Our analysis is more limited in scope, focusing on the internal referential dynamics of the model itself. We thank an anonymous reviewer for highlighting this distinction between our approach and prior contributions.
15. It is worth noting that calibration and validation do not rely solely on induction. By constraining the output space or some parameters, they provide semantic content that goes beyond merely stating an existing regularity. Unfortunately, this may still be insufficient for overcoming the potential issue of equifinality, which limits the value of pure data-driven and bottom-up evaluations of conceptual constituents.
16. Bunge (1973) interestingly outlined two constraints for simulations. Firstly, the simulated object must be *contagiously* analogous to the target, where contagious analogy is defined as having a transitive similarity relation. Secondly, the analogy must possess significance, defined as *valuable* either intrinsically or for a third party. Therefore, according to him simulations are by design analogies.
17. Multiple analogies are defined as several distinct analogies supporting the same conclusion (Bartha, 2010). Nested analogies are analogies that are mediated by a third analogue (Nersessian & Chandrasekharan, 2009). Thus, nested analogies are transitive and refer to different domains.
18. By conceptual transduction we mean the process of structuring the conceptual domain according to the implicit and explicit schemes and rules that convey the overall purpose. We borrow the term transduction from Simondon and Adkins (2020), according to whom

> [b]y transduction we mean a physical, biological, mental, or social operation through which an activity propagates incrementally within a domain by basing this propagation on a structuration of the domain operated from one region to another: each structural region serves as a principle and model, as an initiator for constituting the following region, such that a modification thereby extends progressively throughout this structuring operation. (Simondon & Adkins, 2020, p. 13)

19. The formulation of Dosi et al. (2010) is slightly different but mathematically equivalent.

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No potential conflict of interest was reported by the author(s).

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Appendix

The notion of innovation in the SKIN models

The evolution of kenes within the SKIN model is driven by the dynamic interaction of agents with their environment (e.g. Ahrweiler et al., 2004). Notably, the model diverges from a standard genetic algorithm by lacking an explicit fitness function.

Firms within the SKIN model possess a set of 'units of knowledge,' represented by triplets:

- Capability (C): An integer indicating the overall domain of application, symbolizing the industry.
- Ability (A): A real number representing the sub-field of application, signifying a specific technique involved.
- Expertise (E): A real number denoting the actual expertise of the firm based on Capability and Ability.

The Innovation Hypothesis (IH) is defined as a subset of the knowledge base, encompassing the total set of kenes of each firm. The hypothesized product is defined by a direct mapping of the capabilities and the abilities of the IH, while its own quality is determined by the abilities and the expertise of the IH. Product inputs are determined by mapping a specific subset of the hypothesized product.

The SKIN model incorporates two modes of research:

(1) Incremental Research: Modeled as a random change by one unit of the ability of one randomly chosen triplet. In case of failure, a new triplet is randomly chosen.
(2) Radical Research: Modeled as a random change in one capability of one randomly chosen triplet. Failure prompts the selection of a completely new triplet.

A crucial element to assess compatibility among producers and to establish networks in the SKIN model is advertising, that involves creating a list of the capabilities of the IH of all firms.

The notion of innovation in the K+S models

In the K+S model (e.g. Dosi et al., 2010), the concept of innovation is tied to the technology employed by capital-good firms, denoted as the couple (A_i^τ, B_i^τ), where A signifies the productivity of the manufactured machine-tool, B represents the productivity of the production technique generating the machine tool, and τ denotes the technology vintage.

Firms in the capital-good industry adaptively strive to enhance market shares and profits by improving technology through both innovation and imitation. These processes incur costs, with firms investing a fraction of their past sales to hire workers in research and development (R&D) and to foster innovation and imitation processes. Dosi et al. (2010) assume all capital-producing firms share identical R&D propensity, reflecting sector-specific R&D intensities and the sector-wide nature of innovative opportunities.

In the model, innovation is conceptualized as a two-step process. The first step determines whether a firm i gains access in time t to innovation through a draw from a Bernoulli distribution whose parameter $\theta_i^{in}(t)$ is an increasing function of R&D expenditures.

If a firm innovates, it draws a new machine-embodying technology ($A_i^{in}(t)$, $B_i^{in}(t)$), whose productivities are equal to the ones of the existing technology ($A_i(t)$, $B_i(t)$) times the realizations of two positive beta random variables ($y_i^A(t)$, $y_i^B(t)$), different for each firm and time period:[19]

$$A_i^{in}(t) = A_i(t)y_i^A(t),$$
$$B_i^{in}(t) = B_i(t)y_i^B(t).$$

The support and the shape of the distributions from which ($y_i^A(t)$, $y_i^B(t)$) are drawn depend on technological opportunities: high opportunities, captured by distributions shifted to the right, lead to a higher probability of innovations surpassing incumbent technologies; with low opportunities, represented by distributions shifted towards zero, the probability is higher that innovation leads to 'failed' technologies that are then discarded.