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RESEARCH ARTICLE

Analytic models in strategy, organizations, and management research: A guide for consumers

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Abstract

Research summary: Analytic models are a powerful approach for developing theory, yet are often poorly understood in the strategy and organizations community. Our goal is to enhance the influence of the method by clarifying for consumers of modeling research how to understand and appreciate analytic modeling and use modeling results to enhance their own research. Our primary contribution is a guide for reading analytic models. Using comparisons with other methods and exemplar analytic models, we explore key features as well as counterintuitive aspects and common misconceptions. We also add by illuminating strengths and weaknesses of analytic modeling relative to other theory-building methods. Finally, we identify under-exploited opportunities for pairing analytic models with complementary methods. Overall, our aim is enhancing the influence of analytic modeling by better-informing consumers.

Managerial summary: In this paper, we explore the use of analytic (mathematical) models for developing strategy and organizations theory. Analytic modeling is common in related fields like economics but is often poorly understood among the broader of strategy and organizations community. Whereas existing resources on analytic modeling are geared towards modelers, our aim is to enhance understanding and appreciation of the method among potential consumers of modeling research. We offer three specific contributions in this regard. The first is a guide for reading analytic models, including key features, counterintuitive aspects, and common misconceptions. Second, we clarify the strengths and weaknesses of analytic modeling relative to other theory-building methods. Finally, we discuss promising opportunities for pairing methods.

KEYWORDS

formal theory, game theory, modeling, research methods, theory development

1 | INTRODUCTION

As social scientists, our ability to explain and predict depends on the quality of our theories (Sutton & Staw, 1995; Weick, 1989). One of the most powerful tools in our pursuit of better theory is analytic modeling. An analytic model is an abstract rendering of a more complex reality into a set of mathematical equations based on concepts, relationships, and assumptions (Adner, Polos, Ryall, & Sorenson, 2009). As a means for developing theory, analytic models are common in finance, economics, political science, and to a lesser extent, sociology (Swedberg, 1990; Debreu, 1991; O'Rand, 1992; Stokes, 2005). In contrast, however, their use in the strategy and organizations literature remains more limited. While some scholars use the method to great effect (e.g., Alacer, Dezso, & Zhao, 2015; Casadesus-Masanell & Yoffie, 2007; Jia, 2013; Kaul & Luo, 2018; Panico, 2017; Sakhartov & Folta, 2014), the method is nonetheless poorly understood by many in the broader community, especially relative to its potential and in contrast to related fields.

A number of indicators reflect the state of analytic modeling in the strategy and organizations literature. One is low use. For example, we reviewed the 6,966 articles published in six premier strategy and organizations journals from 2005 to 2019 and found that analytic modeling was the primary research method in just 4% (see Appendix). A second indicator is low citation rate. In particular, our analysis reveals that papers that rely on analytic models receive fewer citations on average (20.6 per paper) than either econometric analyses (34.5) or qualitative research (37.2)—and far fewer than verbal theory and reviews (68.4).[1] A third and perhaps most critical indicator is the perception of analytic modeling in the broad scholarly community. To understand these perceptions, we interviewed 35 strategy scholars across a range of disciplines and surveyed 34 strategy PhD students at seven schools across the United States and Europe. Scholars without training in modeling research (the majority) reported that they rarely read analytic modeling research, regard analytic models as harder to interpret than other methods, and believe analytic models are rarely relevant to their own work.

[1]This pattern holds even when controlling for author affiliation, journal, and year of publication (see Appendix). Moreover, it offers a striking comparison to economics, where as Knudsen, Levinthal, and Puranam (2019) note, formal methods have been a dominant research method since Samuelson (1947).

These indicators reflect a significant, but we believe addressable, challenge: a gap between the producers of analytic modeling research and potential consumers of that work. This gap is exacerbated by diverse doctoral training (i.e., many scholars have little exposure) and the relatively small number of modelers in strategy and related fields. Moreover, potential consumers lack resources to improve their understanding of the method. On the one hand, economics texts (Bolton & Dewatripont, 2004; Gibbons & Roberts, 2013; Tirole, 1988) and modeling texts (Kemeny & Snell, 1962; Mershon & Shvetsova, 2019) discuss the mathematical apparatus of analytic models. Yet, these are often inaccessible or at least little read by general audiences, and assume familiarity with tools and concepts like game theory, equilibrium reasoning, and linear programming. On the other hand, appeals for more modeling (e.g., Adner et al., 2009; Ghemawat & Cassiman, 2007) indicate the strengths of the method, but do not (and are not intended to) provide readers with tools to understand and use modeling research. Thus, a gap exists for those potential consumers who want to better understand analytic models and use published modeling results to inform and enhance their own research.[2]

We aim to enhance the usefulness of analytic models for potential consumers of analytic modeling research, and so address this gap. We do so by clarifying how to understand and appreciate analytic models, as well as how to interpret their results. In developing our insights, we draw on an extensive review of well-cited strategy and organization exemplars and interviews with 17 experienced modelers. We also rely on prior work on theory development (e.g., Knudsen et al., 2019; Makadok, Burton, & Barney, 2018; Montgomery, Wernerfelt, & Balakrishnan, 1989; Pfeffer, 1993) as well as our own work on theory development using other methods (e.g., Davis, Eisenhardt, & Bingham, 2007; Eisenhardt, Graebner, & Sonenshein, 2016; Tidhar & Eisenhardt, 2020). Overall, we rely on a broad set of sources to fill the gap for consumers between technical modeling texts and appeals to the model.

We offer several contributions. Our primary contribution is a *guide* for reading, understanding, and appreciating analytic models. Since our focus is the consumer perspective, we articulate their essential features from this lens. Like any good travel guide, we provide the highlights for how (and why) to read and appreciate analytic models, but not every detail of how to model. For example, we indicate common modeling approaches, and clarify their strengths, weaknesses, and types of insights that consumers might expect. Given our aim, we also emphasize the counterintuitive aspects of analytic models and common misconceptions such as the role of strong assumptions (like rationality) and omitted variables, which we argue are a *strength* of the method rather than a weakness. We also highlight the relevance of what we term the "conceptual narrative," and the specific research questions that analytic models are often used to address. By emphasizing similarities, differences, and complementarities with familiar methods, we use comparison to further illuminate analytic modeling. By using interviews with experienced modelers, we capture some of the art of analytic modeling as well.

A second contribution is *positioning analytic modeling* within the broad repertoire of theory development methods in strategy, organizations, and management research more broadly—that is, what the method is and when it is useful. In particular, we clarify the value that analytic models bring to theory building, including their unique strengths (precision, internal consistency, and transparency) and weaknesses (external validity and role of the modeler). In doing so, we sharpen what consumers can (and cannot) expect to learn from analytic models.

[2]One recent effort to fill this gap is Csaszar (2020), which although geared to potential producers of modeling work contains valuable insights for consumers of that work as well. Knudsen et al. (2019) is similarly a parallel effort.

A third contribution is *pairing analytic modeling* with other well-known methods in strategy and organizations research—that is, how to leverage analytic modeling in conjunction with other methods. We note how analytic modeling complements (a) methods for theory building, including verbal theory, theory-building from cases, and simulation, and (b) methods for testing theory, such as econometrics. We also identify opportunities for pairing research methods. For example, we observe a strong complementarity with theory-building cases, which can provide fresh (yet often imprecise) insights that analytic modelers can then unpack and rigorously explore. We similarly note substantial (yet largely untapped) opportunities for pairing analytic models with machine learning. The latter excels at identifying empirical patterns but often lacks insight into underlying mechanisms. Overall, we contribute a rich view of pairings among methods and their distinct roles in research.

Collectively, our goal is to fill the gap between technical texts and appeals to model. Unlike prior work, our focus is squarely on providing value to *consumers* of analytic modeling. In contrast with texts, we offer simplicity and focus on the essential facets, supported by contemporary exemplars, comparison with other methods, and emphasis on counterintuitive and confusing aspects of the method from the consumer perspective. In contrast with appeals to model, we provide insight into how to understand analytic models and use their results.

We begin by describing analytic modeling (e.g., definition, comparison with other theory building methods, strengths, and weaknesses). We then develop our guide to reading, understanding, and appreciating analytic modeling research. We conclude by exploring using analytic models in the future with other methods and in the era of "big data" (Table 1).

2 | POSITIONING ANALYTIC MODELING

2.1 | What is an analytic model?

A model is an abstract rendering of a more complex reality (Knudsen et al., 2019; Lave & March, 1975) that includes assumptions, logic, and consequences (i.e., outcomes). Our focus is on analytic models, which formalize this abstraction into a set of mathematical equations based on concepts (e.g., from strategy, economics, and organization theory), relationships among those concepts, and assumptions. The goal of an analytic model is to capture the fundamental properties (e.g., strategic interactions, economic incentives) of a complicated reality in a "small world" that can be readily analyzed (Savage, 1954). The modeler then analyzes this model through closed-form analysis, by manipulating the equations and/or using proofs to validate propositions and identify boundary conditions (Adner et al., 2009). Alternately, the modeler may use numerical analysis by assigning values to the variables in the equations and calculating the resulting outputs, which are often displayed graphically.

Analytic models differ from other theory-building approaches in both setup and analysis. Like analytic models, *simulations* are formal representations. Simulations, however, typically lack an analytic setup. Instead, they encode variables and decision rules in software, seed variables with numeric values, and then run the code over multiple periods and seedings (Davis et al., 2007; Harrison, Lin, Carroll, & Carley, 2007).[3] The goal in doing so is to illuminate the

[3]A recent editorial (Knudsen et al., 2019) argues that distinctions between these modeling approaches may not productive. As they rightly argue, analytic modeling, and simulation share a form (i.e., formal characterization of a complex reality) but differ in technical implementation. We agree. Yet, our interviews and surveys also reveal that

TABLE 1 Guide to understanding analytic models

Element	Rationale	Value to consumer	Key considerations
Research question	Focuses modeling effort on a single idea, core tradeoffs/ tensions	Faster and better understanding of the purpose of the analysis and insight into the researcher's choice of analytic modeling Indicates what one is likely to learn from the analytic model	Fit of research question with an analytic model Core tensions/tradeoffs of interest
Articulated conceptual narrative	Interpretive step for consumers between the research question and mathematical model Links research to real-world phenomenon	Confirms relevance of phenomenon Foreshadows constructs, relationships, and logic of the mathematical model Conveys intuition of results and provides a touchpoint as math unfolds	Constructs included (and not) in the narrative Vividness of narrative example (intriguing or well-known) Assumptions implicit in the narrative Precision of research question, constructs, and logic of the narrative
Modeling approach	Provides overarching structure of the analytic model	Faster and better understanding of what to expect from the analysis Insight into why the researcher chose a particular approach	Assumptions, strengths, and weaknesses of various approaches Types of insights the given approach is able to produce
Mathematical model	Provides model setup (constructs, relationships, and assumptions) that sets the stage for the analysis	Clarifies what constructs are in the model vs. what is "controlled" through exclusion Clarifies mathematical representations of relationships Clarifies the assumptions that affect the analysis and determine boundary conditions	Number of constructs Choice of constructs to exclude Abstraction of constructs Mathematical representations fit with theoretical definitions Appropriate assumptions
Model analysis	Develops logical implications of model setup using analytic and/or numeric solutions Isolates specific results, e.g., with staged analysis and comparative statics	Indicates primary insights of model Faster and better understanding when alert to insight at each stage of the model Faster and better understanding when alert to equilibrium outcomes and the conditions under which they occur	Choice of analytic vs. numerical analysis Organization of each stage of the analysis Choice of parameters that may affect specific equilibrium outcomes
Model validity	Confirms internal validity through audit trail Builds intuition about external validity via model extensions like supplemental numeric analysis and matching outputs to real data	Gain confidence in the internal logic of the model Gain confidence that the model provides valid insights into the real world	Choice of numeric values to use in a numeric supplement to analytic analysis Match of real-world empirical data to important features of model setup

patterns that emerge from the interaction of (potentially many) variables, especially over time. In contrast, the setup of an analytic model lays bare precisely how the variables and parameters that comprise the model relate to one another, and the subsequent stepwise analysis of the model's equations allows the reader to (in principle) recreate the analysis in real time. Thus, relative to simulation models, analytic models provide an "audit trail" (Adner et al., 2009) that increases understanding of why and when outcomes occur.

Analytic models also differ from *verbal theory*, including that which emerges from *theory-building cases*. These approaches rely on logical arguments that the theorist conveys in natural language, which are, for the latter, grounded in empirical data (Eisenhardt et al., 2016). Verbal theorists typically define theoretical constructs, describe relationships, and support those relationships with logical arguments, often by referencing prior theory and empirical work. For theory-building case methods, the theory is emergent from data and rests on iterative analysis among data, emerging theory, and prior research (Eisenhardt, 1989). In contrast, analytic models use mathematical (rather than natural) language for definitions and use mathematical operations to step through the analysis. So, while analytic models and verbal theory models have similar outcomes, their mechanics are quite different.

In practice, analytic models typically address distinctive research questions and yield distinctive contributions relative to these other methods. For example, simulations are often used to uncover *what* patterns emerge from the interactions of constructs, especially, over time (Burton & Obel, 2011). By comparison, analytic models often address *why* (causal mechanisms) or *when* (boundary conditions) these patterns occur. Similarly, while verbal theory may address how constructs interact and why patterns occur, analytic models are generally better equipped to identify nuanced or counter-intuitive interactions among a few constructs. Finally, questions in theory-building case research are frequently open-ended to "leave room" for emergent constructs and theoretical relationships, and to explore *how* processes unfold (Eisenhardt & Graebner, 2007). In contrast, research questions in analytic modeling are typically narrower in scope (e.g., when will a result occur, or what is the optimal choice given a set of inputs).

2.2 | Strengths and weaknesses of analytic models

2.2.1 | Strengths

Analytic models have several unique strengths. First, they are precise. This precision derives from use of mathematical arguments. To construct a model, the modeler must articulate precise mathematical definitions for all constructs and relationships (Freese, 1980). Moreover, models include *only* those constructs specified by the modeler. This allows models to act as mathematical laboratories, in which modelers isolate and rigorously define a set of constructs and then trace their logical implications. Moreover, like laboratory studies, models are able to mitigate data issues such as availability and confounds, and rivet attention on the specific mechanisms of interest. This strength was famously summarized by George Box (1976), who wrote that while all models are wrong, some are useful. Analytic models are "wrong" in that they are at

analytic models face unique challenges specifically because lack of understanding regarding their *technical implementation*. The two methods also differ in how they create value in theory building. Thus, we focus here on analytic models, whether solved analytically or numerically.

best approximations of the real world, but they are useful because they can allow a researcher to unpack a phenomenon in a way that might otherwise be impossible.

A subtler point is that mathematical precision is also valuable because it allows modelers to be precise in their predictions. For example, a verbal theory model might describe X_1 as an increasing function of X_2, while an analytic model might instead posit that $X_1 = bX_2$, where b has clearly articulated properties. This precise relationship is in turn more readily subjected to empirical testing and falsification (Csaszar, 2020). Whereas verbal theory might allow many specifications and transformations of variables, theory from analytic models can thus often stand or fall on the result of a single test.[4] Falsifiability is central to effective theory-building, which suggests, paradoxically, that a key strength of analytic models is their ability to be proven wrong (this value was perhaps best articulated by Freeman Dyson (2004), who wrote that "since progress in science is often built on wrong theories that are later corrected, it is better to be wrong than to be vague," see also Popper, 1962 and Montgomery et al., 1989).[5]

A second strength is that analytic models have internal logical consistency. Mathematical operations ensure that outputs flow directly from inputs and are thus the unequivocal logical implications of these inputs (Coleman, 1964; Oxley, Rivkin, & Ryall, 2010). This means that analytic models are likely to be particularly valuable whenever the interactions between variables is difficult to predict, or more broadly wherever intuition is likely to lead one astray. This may be due, for example, to complexity (e.g., outcome A is a function of inputs B, C, D, and E), indirect effects (e.g., A affects B and C, C also affects B), or interactions across levels of analysis.

Makadok and Ross (2018) illustrate as follows. From prior work, the authors observe that since firm capabilities underpin competitive advantage, better capabilities should yield higher returns. They then note, however, that higher returns may attract new entrants, which in turn could hurt the focal firm. By constructing an analytic model, the authors identify when a firm's investment in improving its own capabilities may actually hurt its performance. An analytic model works well here, and yields a counterintuitive result, because verbal theorizing is likely to miss the subtle interaction of direct and indirect effects—that is, positive *direct* effect (decreasing costs) may be swamped by a negative *indirect* effect (increasing competition from new entrants).

Finally, analytic models are transparent. That is, the inputs and steps of the analysis provide an "audit trail" (Adner et al., 2009) that uniquely (a) allows the analysis to be verified by the reader in real time, and (b) illuminates the influence of specific assumptions or constructs (e.g., whether an assumption is necessary for a result to hold). Thus, relative to other methods, the discipline of the audit trail can allow clear insight into why a given result emerges. A related insight is that much of the value of an analytic model is created simply by the set up—i.e., by forcing the researcher to articulate transparently and precisely the relevant assumptions, constructs, and relationships. Thus, analytic models can provide substantial theoretical clarity (for both modeler and readers), even prior to any analysis.

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[4]An important caveat to this argument is that the functional forms that comprise a model (e.g., $X_1 = bX_2$ in the example above) may be chosen for a variety of reasons, including both fit with theory and mathematical tractability. In the latter case, the failure to empirically verify the model setup or its predictions may not falsify the theory, but instead calls into question the specific functional form used. We thank the Editor for clarifying this point.

[5]For this reason, econometric researchers sometimes develop mathematical hypotheses for empirical testing. One example is Ethiraj (2007), who uses an analytic model to offer precise predictions about investment and innovation performance.

2.2.2 | Weaknesses

Yet like all methods, analytic modeling has weaknesses. These primarily relate to the need to translate a real-world phenomenon into math. One concern is external validity: to the extent that critical inputs are missing or assumptions are unrealistic, the model risks representing a "toy" problem that sheds little insight into the real world. In contrast, empirical methods like econometric research and theory-building cases benefit from a direct tie to phenomena through their data. More broadly, the assumptions and simplifications needed to render complex real-world phenomena in math often results in models that for many consumers seem distant from reality, hard to read, and difficult to remember.

A second weakness is that analytic models rely solely on constructs and relationships defined by the modeler. Thus, relative to theory-building case studies, for example, models are particularly constrained by how the modeler conceptualizes the phenomenon. Hannah and Eisenhardt (2018) illustrate as follows. The authors ask how firms navigate ecosystem industries comprised of multiple components. A rich body of prior modeling research on this topic had identified two strategies: (a) entering and integrating across multiple components, or (b) entering one component and relying on partners for the other. In contrast, Hannah and Eisenhardt (2018) construct a multiple case study of the solar industry, and in doing so identify a third: (c) entering components sequentially over time. Extending existing research in this way was possible because prior modeling work framed the entry decision as a single, static choice.[6]

2.3 | Common misunderstandings

In contrast, two of the most common critiques of analytic models—that is, that they (a) lack realism, and (b) are driven by unrealistic assumptions—in fact reflect a misunderstanding of the method. Similar to experimental laboratory studies that isolate a given set of variables, lack of realism (e.g., missing predictors) and strong assumptions (e.g., rational actors) are central to how analytic models contribute. Dushnitsky (2010) illustrate as follows. The author notes that entrepreneurs have two options when courting investors: they can disclose their inventions ("you evaluate my invention and decide whether to invest") or by adopt a contingent payment scheme ("you invest, and I will only get paid if it works"). Whereas prior research examined this choice as a function of potential opportunism, Dushnitsky asks what happens if entrepreneurs are honest, but overoptimistic. His model—with rational, perfectly-honest actors—is unrealistic, but nonetheless illuminates considerations that would be nearly impossible to unpack empirically.

More broadly, models necessarily depart from reality, so the question is not whether they are realistic but whether their simplifications are useful (Nelson and Winter, 1982; Savage, 1954). For scholars not trained in the method, however, this can be challenging to assess. With this in mind, we now turn to our guide for how consumers can understand and appreciate analytic models and use analytic modeling results in their own work (Table 2).

[6]For an excellent exploration of this issue, we refer interested readers to Menon (2018), which provides insight and examples of how the setup of cooperative game theory models can profoundly shape model output.

3 | A GUIDE TO UNDERSTANDING ANALYTIC MODELS

3.1 | Appropriate research questions

Like all research, analytic modeling starts with a research question that defines the purpose of the analysis. A common theme in our interviews with experienced modelers is that effective research questions are usually simple. As one modeler said, "Each formal model is about a single idea." Another described the necessity of asking, "What complexity can we ignore?" A related theme is that effective questions often have a central trade-off or tension that models can unpack to reveal how different forces interact and what governs their resolution. As one modeler explained, "Any sensible model has a tension in it, otherwise you only get corner solutions."

Specific research questions addressed in analytic modeling often fall into several broad categories. Understanding these types (and whether a given analysis addresses one) is useful for consumers to gain a faster and better understanding of (a) the purpose of the analysis, and (b) why the researcher chose analytic modeling. These categories are (a) causal mechanisms, (b) boundary conditions, (c) optimal decisions, and (d) phenomena with limited data.

3.1.1 | Causal mechanisms

Analytic modeling questions often unpack why a phenomenon or result occurs. This may be especially useful when several mechanisms are likely to be at play. Examples include why rival firms collaborate with rivals to develop compatible products (Adner, Chen, & Zhu, 2019) or why investors use particular contract designs (Dushnitsky, 2010). Analytic models are useful here because they allow: (a) control for alternative explanations and interacting processes by including or excluding these factors from the model, and (b) transparency into how constructs interact and why outcomes occur.

Sakhartov and Folta (2014) illustrate as follows. The authors note that there is a wealth of evidence for the positive impact of related diversification on firm value. Relatedness impacts firm value, however, through two distinct and often conflated mechanisms—resource synergies across businesses in real time, and redeployability of resources among businesses over time. With an analytic model, the authors are able to (a) identify the effects of synergy vs. redeployabilty, and (b) illuminate how and why various constructs impact each. For example, market uncertainty enhances the value of redeployability (but not synergy) by allowing firms to more easily withdraw their resources from underperforming markets. They also identify the bias incurred by conflating synergy and redeployability. This distinction had eluded prior researchers largely because of the difficulty in disentangling the two factors empirically.

3.1.2 | Boundary conditions

Related to the above, analytic modeling questions often address *when* a given outcome or theory holds. This is particularly useful given conflicting theoretical predictions or countervailing empirical results in prior work. Analytic models are effective because they can precisely specify

TABLE 2 Recent examples of analytic modeling research

Study	Research Question	Approach	Key Constructs	Representative Findings
Kaul & Luo (2018)	How do CSR activities affect firm profits and social efficiency?	Non-cooperative game theory	Resource characteristics Demand characteristics	CSR improves firm profits and social efficiency if and only if activities are closely related to core firm activities and don't substitute for activities of non-profits.
Alcácer, Dezsõ, and Zhao (2015)	When will firms co-locate with rivals given the tension between learning and competition?	Non-cooperative game theory	Market attractiveness Knowledge fungibility Location choice	Firms prefer to avoid co-locating when markets are similar, and may co-locate when one is more attractive than another. Similarity in capabilities also increases co-location.
Adegbesan (2009)	How is the value created by complementary resources allocated?	Coalitional game theory	Resource complementarity Industry structure	Allocation of value (value capture) between firms is a function of industry structure and resource characteristics
Obloj & Zemsky (2015)	How do various contract designs affect division of value in buyer-supplier relationships?	Coalitional game theory (Biform game)	Efficiency Transactional integrity Incentive alignment	Neither buyers nor suppliers have incentives to use contract designs that fully maximize joint value creation.
Chan, Nickerson, & Owan (2007)	How can firms optimally manage their R&D pipelines given the need to keep assets utilized?	Decision-theoretic model	Transaction costs Project characteristics Risk preferences	The thresholds for advancing projects differ by the state of the firm's pipeline, the magnitude of transaction costs in the technology market, and the magnitude of adjustment costs.
Puranam, Gulati, & Bhattacharya (2013)	When is it optimal to both make *and* buy an input?	Decision-theoretic model	Scale economies Complementarity Transactional hazards Production costs	Plural sourcing is optimal when either the complementarity between modes or the constraints associated with one mode are strong relative to transaction costs.
Cowan & Jonard (2009)	Under what conditions will alliance networks exhibit small-world properties?	Custom model w/ high level of aggregation	Firm knowledge stocks Alliance costs	Small world networks form when firms value moderate knowledge overlap with partners
Baldwin & von Hippel (2011)	When are product innovations by user innovators or open collaborations viable?	Custom model w/ high level of aggregation	Design costs Design architectures Communication costs	Falling design and communication costs make certain types of innovation, such as open collaborations, more feasible.

how individual constructs affect the results, and because their proofs can illuminate whether specific assumptions are necessary for a result to hold.

For example, MacDonald and Ryall (2018) ask how new entrants into an industry affect the profitability of incumbents. They observe that the effect is unclear because of two countervailing effects, both of which have empirical and theoretical support. On the one hand, entrants (a) create economic value by bringing new capabilities to an industry. On the other hand, they (b) increase competition for incumbents. With an analytic model, the authors determine that the value added by entrants determines which effect dominates. They then calculate threshold values for when an entrant will increase or decrease incumbent profits. In doing so, the authors reconcile the tension of conflicting effects and develop an integrative theory.

3.1.3 | Optimal decisions

Analytic models also often explore questions related to optimal strategic decisions. That is, they are uniquely positioned to identify (a) an optimal choice or action given a set of assumptions, and (b) *why* and *when* that choice shifts. In contrast, empirical methods and simulation are limited to identifying high-performing choices that exist in their real (or simulated) data, and may provide less insight into why and when those actions are optimal. For example, Puranam et al. (2013) ask when it is optimal for firms to engage in plural sourcing—i.e., both making and buying a given component. They construct an analytic model that describes total firm costs as a function of the marginal costs of each mode, transaction costs, production constraints, and complementarities across modes. Their subsequent analysis then indicates (a) when plural sourcing is optimal, and (b) why the optimal mix of internal and external sourcing varies across situations. The result is a benchmark against which researchers can compare with outcomes based on different assumptions.

3.1.4 | Phenomena with limited data

Analytic models are also effective for questions related to phenomena for which limited data preclude empirical study. For example, this may be due to (a) difficulty collecting data or empirically controlling for correlated variables, or (b) rarity or novelty. For example, Adner et al. (2019) examine why rival firms might make their products cross-compatible. They begin by noting the existence of the Kindle e-book reading app for Apple's iPad, despite Apple's having its own rival iBooks app. They also observe that a difference between the firms is profit centers: Apple profits from both hardware and book sales, while Amazon sells its hardware at cost and profits solely from book sales. With an analytic model, the authors identify the conditions under which a firm will permit cross-compatibility as a function of the utility and profitability of both hardware and content. In contrast, a similar study using statistical methods might be difficult to conduct because of too few observations.

3.2 | Articulated conceptual narrative

Another common theme in our interviews with expert modelers is the importance of grounding the analytic model in a real-world phenomenon. For example, one prolific modeler noted “the best models grapple with reality" while another observed "data need to discipline the model." A third argued that "if the phenomenon is real, you should be able to find it in the real world and you shouldn't have to look too hard." Many also spoke about including a description of the real-world phenomenon in their papers to convey its relevance and create stickiness (i.e., to make the model memorable). While not all modelers use or include this type of description, many do. We term this description a *conceptual narrative*.

Some conceptual narratives are simply motivating examples, but those that are more useful for consumers articulate the core features of the focal phenomenon through the lens of the research question. Thus, they provide an interpretive step for consumers between the research question and the mathematical model by clarifying the constructs, relationships, and underlying cause-and-effect logic to be modeled. Relative to simple motivating examples, conceptual narratives are both richer and narrower in that they highlight certain elements of the phenomenon and ignore others. The result is to provide the reader with a better understanding and definition of the relevant constructs and relationships, and the research question itself.[7]

For readers, understanding the conceptual narrative has several functions. One function is to confirm that the phenomenon is real and worth studying. This is useful because analytic models lack their own data; consumers may thus be skeptical of the phenomenon's importance or even existence, especially for novel phenomena and under-theorized settings. In contrast, a vivid conceptual narrative can motivate interest in reading a potentially useful model and facilitate recall of its results. This is particularly true when the real-world phenomenon is intriguing (e.g., sport kayaking), well-known (e.g. Wintel), or both.

For example, Lieberman, Lee, and Folta (2017) ask how resource redeployability (the potential for multi-business firms to redeploy resources from one internal unit to another) impacts market entry and speed of market exit. The authors ground their model in a clear and memorable comparison of two failed projects at Proctor & Gamble (Olay Cosmetics, and Olestra, a fat substitute). In the former, P&G's ability to redeploy its human and physical capital to existing businesses led to a quick exit, whereas in the latter the lack of internal applications for the Olestra production plant led to a slower exit and a steep loss. This explicit narrative highlights a significant instance of the phenomenon, thus confirming its strategic relevance for readers and grounding the mathematical model in an important and real context.

A second (and more important) function of the conceptual narrative for consumers is to clarify what constructs, relationships, and assumptions are relevant, and the rationale for these choices. For example, Baldwin, Hienerth, and von Hippel (Baldwin, Hienerth, & Von Hippel, 2006) ask when users vs. firms create innovations. Prior to setting up their model, the authors provide a conceptual narrative of the innovation history of sport kayaking. This narrative articulates the history in terms of the constructs relevant to the research question like features of innovators (e.g., motivations of users vs. firms) and innovations (e.g., design complexity and cost). These features then become the central constructs of the analytic model, while other potential factors (e.g., consumer preferences) are excluded from the narrative and later the model. Thus, the conceptual narrative is particularly useful for readers because it foreshadows the mathematical model.

[7]Our use of the term narrative reflects its use in related works, such as Mershon and Shvetsova (2019) and Shiller (2019: xi), who describe narratives as "stories or representations used to give an explanatory or justificatory account." In this view, a narrative is a fundamental interpretive construct that gives meaning to observed reality by mapping events to theory (Mershon & Shvetsova, 2019: 38).

Finally, understanding the conceptual narrative can clarify the intuition behind the results. This makes the model results more understandable, easier to remember, and more likely to be useful. It also provides a critical touchpoint for continued understanding as the analysis unfolds. For example, Pacheco-del-Almeida and Zemsky (Pacheco-de-Almeida & Zemsky, 2012) ask why some firms make their intellectual property available to rivals. Their conceptual narrative describes Intel's rivalry with AMD in microprocessors. A key aspect of this narrative is that (a) formal IP protection is relatively easy to circumvent, but (b) there are nonetheless substantial diseconomies for technology laggards to "catch up." The authors thus construct a model that pits a laggard (i.e., AMD) against a leader (i.e., Intel). Analysis of this model leads to the surprising result that leaders can benefit from disclosing its IP, but laggards are actually better off when leaders do not. The conceptual narrative provides a plausible rationale for this counterintuitive mathematical result: Intel gave AMD access to its intellectual property, but then restricted it, which forced AMD into costly head-to-head competition. It also provides insight into potential boundary conditions: this result is more likely to apply in settings where imitation is possible and less so where intellectual property is difficult to circumvent (e.g., pharmaceuticals).

Conceptual narratives are sometimes explicit, and thus easy to identify. For example, they may be presented as detailed case histories (e.g., the innovation history of sport kayaking, in Baldwin et al., 2006). More often, they are shorter descriptions that nonetheless convey the essence of the focal phenomenon using a well-known and/or intriguing real-world example (e.g., Casadesus-Masanell & Yoffie, 2007; Makadok & Ross, 2018). In other cases, however, they may be more subtle. This is particularly true for well-established theoretical paradigms (e.g., Chatain & Zemsky, 2011; Cowan & Jonard, 2009), where relevant constructs and assumptions are more likely agreed upon. Even here, however, identifying and understanding a real-world case can be a way to link reality to the mathematical model in a meaningful way, clarify the relevance of the research question, and create a touchpoint for the unfolding analysis.

In contrast, ineffective (for consumers) conceptual narratives are vague or thin. They may simply show that a phenomenon exists or be a vague story that blurs key features. They may rely on "toy" constructs like "widgets" that make the analysis seem less relevant. Overall, conceptual narratives are valuable for consumers because they link reality to the mathematical model in a conceptually meaningful and intuitive way, and foreshadow the mathematical model.

3.3 | Modeling approach

The modeling approach is the structure within which an analytical model is expressed and mathematically analyzed. Modeling approaches are valuable for readers to identify and understand because they provide the overarching structure of the analytic model. That is, just as the selection of an econometric (e.g., OLS vs. logit), simulation (e.g., system dynamics vs. NK), or machine learning (e.g., random forest vs. decision trees) approach shapes the analysis, so too does the choice of modeling approach. Several modeling approaches are common in strategy and organizations research, each fitting different phenomena, different research questions, and able to produce different insights. By understanding these approaches (at least at a high level), readers can gain a faster and better understanding of (a) what to expect from the analysis and (b) why the researcher chose this approach. One way to categorize these approaches is by number of decision makers (agents) in the analysis (see Table 3).

3.3.1 | Single-agent models

Some models, often termed *decision-theoretic models*, examine decisions faced by a single agent. They are useful for calculating the optimal choice when decisions are affected by multiple variables acting in subtle or complex ways such that the best choice would be difficult to identify with verbal theory. Decision-theoretic models typically yield insights into (a) the optimal decision and (b) how various factors affect that choice.

Decision-theoretic models typically have five parts: (a) outcome variables (e.g., profit, cost), (b) decisions variables under the agent's control (e.g., production quantity) and (c) parameters not under its control (e.g., market size). The relationship among these elements is described by (d) an objective function, which is optimized subject to (e) constraints, which are conditions that must be met by an optimal solution (e.g., a budget that cannot be exceeded). Analysis then involves optimizing the objective function with respect to the decision variable(s), usually by solving a series of simultaneous equations and/or with decision trees.

Harris and Raviv (2002) illustrate as follows. The authors ask when firms should adopt a particular organizational design (i.e., flat, functional, divisional, and matrix). Prior research argues that any of these designs may be successful, but it is unclear *why* or *when* each is optimal. The authors thus build a model in which a firm (modeled as a single agent) needs to complete a set of tasks. The firm can do so by adopting one of the four organizational designs. Each design incurs unique opportunity and salary costs, and enables different degrees of coordination. By analyzing how these variables interact, the authors provide insights into when each design is optimal. For example, a flat organization is preferable when salary costs are high.

The decision-theoretic approach is particularly powerful when a *single* decision-maker faces a clear choice among several alternatives (e.g., distinct organizational designs). Since decision-theoretic models typically represent other actors (e.g., suppliers, consumers) simply or not at all, they are most useful when these actors are either less relevant (e.g., a student deciding which classes to take), or can be summarized either in aggregate (e.g., suppliers always sell at cost) or through the constraints (e.g., executives set the R&D budget, but do not otherwise affect project selection). Research questions are often phrased in terms of the optimal strategy, such as optimal investment in R&D (Chan et al., 2007) or sourcing mode (Puranam et al., 2013).

3.3.2 | Models of multiple interacting agents

Many questions in strategy and organizations research address interactions among interdependent agents. The family of modeling approaches that examines these interactions is game theory. Two approaches are common in strategy and organizations research: *non-cooperative game theory* and *coalitional game theory*.

Non-cooperative game theory (NGT) examines the actions and counteractions that agents take given their understanding of the likely behaviors and responses of the other agents in the model. Thus, it fits settings in which a well-defined population of agents interacts through well-defined possible actions, and where the outcomes of any one agent's actions depend on the actions of other agents. Common applications include rivalry in oligopolistic markets or auctions—situations in which agents try to anticipate (and are affected by) the actions others.

NGT models typically consist of (a) a set of agents, (b) a set of actions available to each agent, and (c) payoffs to each agent as a function of the actions taken by every agent. Analysis of an NGT model generally involves determining the best response function of each agent—that is, its preferred action given every possible action by every other agent. The full set of best response functions (one for each agent) creates a set of equations that can be solved to determine possible equilibria (sets of actions from which no agent has an incentive to unilaterally deviate). The goal of the analysis is then to provide insight into what equilibria arise and when.[8]

For example, Panico (2017) asks how the degree of synergy in an alliance (i.e., surplus value relative to remaining independent) and control configuration (i.e., which firm controls alliance resources) affects firms' willingness to ally with one another. To address this question, he models two firms. Each firm can either (a) remain independent or (b) form an alliance. If the firms do form an alliance, they also choose how much to invest in (c) joint alliance activity vs. (d) improving their own market position. Each firm seeks to maximize its own objective function, which reflects model parameters (e.g., value of synergy, probability that the firms will renew their alliance) and the actions of the other firm. The analysis then indicates when the firms form an alliance and how each allocates its resources. For example, greater synergy increases alliance formation, but also encourages more investment in one's own market position.

A second game theory approach is *coalitional game theory* (CGT). In contrast to NGT, CGT removes the details of the interaction to focus on how different coalitions (i.e., subsets) of agents create and capture value (Ross, 2018). Thus, agents do not take actions or counteractions. Rather, value creation and capture depend on the presence of particular agents in a given coalition. To illustrate, a model of buyers and suppliers like Jia (2013) might have three agents: a high-quality supplier, a low-quality supplier, and a buyer. The analysis would then identify possible coalitions, as well as how value is created and allocated in each (e.g., coalitions that do not include the buyer might result in no value being created).

CGT models consist of (a) a set of agents, (b) a characteristic function that maps each coalition of agents to the value it can create, and (c) and a solution concept that defines how the value created by a particular coalition is allocated among its members. Thus, unlike NGT, CGT does not specify the specific actions or counteractions agents take. Instead, CGT focuses on the possible coalitions that can form (and their value creation) and how this influences competition (and thus agents' value capture) (Gans & Ryall, 2017). Because it abstracts away from the "procedural details" of agents' interactions, CGT is thus particularly valuable when the details of the bargaining process are either unknown or not central (Ross, 2018).

Adegbesan (2009) illustrate as follows. The author examines how gains from trade are distributed in strategic factor markets. He addresses this question through a CGT model known as an "assignment game" (Shapley & Shubik, 1972), in which a population of agents (firms) buys and sells resources. Value is created when resources are matched to a productive use (e.g., the buyer of a resource values it more highly than the seller). By varying characteristics like resource complementarity and the number of firms, the analysis reveals who benefits from trade. For example, whereas prior research posited that superior knowledge of resource value was necessary to capture value in strategic factor markets, Adegbesan finds that firms need only to have idiosyncratic complementarity (i.e., to value resources more highly) to do so.

[8]Since NGT models represent the actions and outcomes available to each agent, they are often sensitive to details of the setup (e.g., order of moves, available information, and beliefs of the agents). This is both a strength and a weakness. In auction models, for example, researchers can examine how changes to the auction format affect what strategies agents employ (Makadok, 2001; Ross, 2012). In other cases, however, specific modeling choices may not be central to the theory and may instead be chosen for modeling expediency; robustness checks to understand the implications of these choices are thus valuable. See Ross (2018).

TABLE 3 Comparison of modeling approaches

Focus	Examples	Common Questions	Key Assumptions	Theoretical Logic	Useful References
Single agent models Decision-theoretic models					
Single agent perspective Optimal decision-making especially in complex or non-linear settings	Chan et al. (2007), Harris & Raviv (2002), Puranam et al. (2013), Van den Steen (2017)	What is the optimal decision?	Single relevant agent Clear alternatives	Optimal decision can be computed as a function of known constructs and constraints	Rapoport (1998), Peterson (2017), Kreps (1988)
Multiple agent models Non-cooperative game theory (NGT)					
Multiple agent perspective Strategic interaction between multiple, self-interested agents Focus on actions and counteractions	Alcácer et al. (2015), Bennett & Levinthal (2017), Luo et al (2018), Gambardella et al. (2015), Kaul & Luo (2018), Puranam & Swamy (2016), Baron (2018), Schmidt et al (2016), Panico (2017), Hagiu & Spulber (2013), Asmussen & Fosfuri (2019)	What is the equilibrium price or industry structure? What is the optimal competitive strategy?	Agents behave rationally Interdependent outcomes Game is fully specified (i.e., actions and payoffs can be determined)	Interdependent outcomes require agents to anticipate one another's behavior	Gibbons and Roberts (2013), Camerer (1991), Rasmusen (2006), Luce and Raiffa (1989)
Multiple agent models Coalitional game theory (CGT)					
Multiple agent perspective Impact of competitive environment on value creation and capture	Adegbesan (2009), Lippman & Rumelt (2003), Jia (2013) MacDonald & Ryall (2004), Chatain & Zemsky (2007; 2011), Obloj & Zemsky (2015), Adner & Zemsky (2006)	How does industry structure influence who captures value?	Interdependent outcomes Agents in coalitions create value	Relative bargaining power determines distribution of value	Ross (2018), Gans and Ryall (2017), Brandenburger and Stuart (2007); Menon (2018), Lippman and Rumelt (2003)
Models at higher level of aggregation Mixed approaches					
System perspective Flexible approach for a various questions and theoretical logics	Denrell et al (2018), Baldwin & von Hippel (2011), Cowan & Jonard (2009), Le Mens et al (2011), Granovetter (1978)	When is a focal phenomenon likely to occur?	No specific assumptions, generally system level of analysis	No specific theoretical logic	Luenberger (1979), Lave and March (1975), Jackson (2004)

Note: We adopt this typology because it yields clear insight into the fit of modeling approach with research question and conceptual narrative, reflects consistent distinctions among approaches, and is commonly used. In contrast, other important characteristics such as timing are often relaxed or blurred.

Researchers using NGT often build on established "workhorse" models. For example, NGT modelers might use an existing model for oligopolistic markets like a Bertrand or Cournot model (Asmussen & Fosfuri, 2019; Cabral & Villas-Boas, 2005), auctions (Chatain, 2014; Makadok, 2001), or principal-agent interactions (Makadok, 2003; Ross, 2014). Workhorse models offer a well-established base and often summarize basic strategic dynamics.[9] Similarly, CGT models typically employ common solution concepts like the core, Shapley value, or nucleolus. Like NGT workhorse models, solution concepts rely on distinct assumptions about how agents interact (e.g., Shapley value assumes contracts can be enforced).[10]

3.3.3 | Models at higher aggregation levels

Some models examine how systems function. In this category, the entity of interest is at a higher level of aggregation, such as network structure (Granovetter, 1978), industry configuration (Baldwin & von Hippel, 2011), or organizational population (Denrell et al., 2017; Le Mens et al., 2011). Models in this category are often custom-built, more often descriptive than models using other approaches, and often provide less insight into the decision making of individual agents. They are particularly useful for describing the structure and dynamics of systems governed my multiple, interacting parameters.

Cowan and Jonard (2009) illustrate as follows. The authors ask when alliance networks will exhibit "small-world" properties (i.e., dense network clusters with short overall path length). They motivate their analysis with the contrasting views on the drivers of alliance formation found in the network literature (social capital) vs. the innovation literature (knowledge access). Their model then describes a set of firms, each with its own knowledge portfolio, that form alliances as a function of the degree of knowledge overlap with potential partners. This yields a network graph that the authors analyze for small-world properties. In doing so, they reach the surprising conclusion that small world networks can arise even in the absence of social capital.

3.4 | Mathematical model

The mathematical model combines the modeler's understanding of the phenomenon or problem (i.e., their implicit conceptual narrative) and the modeling approach. The first step of the modeling process that consumers should understand is the *model setup*—, constructs, relationships, and assumptions—because the model setup sets the stage for the analysis to follow. In fact, the importance of understanding the model setup is a common theme in our interviews with experienced modelers. In a typical comment, one told us, "Once one understands the setup, the results of the analysis are often fairly straightforward." So, while tracing the analysis will improve understanding, the setup is useful on its own. This is a particularly critical insight for consumers who may not wish to follow the technical details.

[9]A common misconception is that workhorse models describe a particular setting. Instead, they capture a particular dynamic or cause-and-effect mechanism. For example, auction models describe how scarce resources are allocated across multiple agents, making them useful for exploring strategic factor markets, not just auctions (e.g., Makadok, 2001; Ross, 2012).

[10]For details on NGT and CGT, see excellent reviews by Ross (2018), and Gans and Ryall (2017). See Brandenburger and Stuart (2007) for *biform games*, an approach that combines NGT and CGT and is a common application of CGT in strategy research.

3.4.1 | Constructs

One element of the setup is which constructs will be included in the model. Here, the research question, literature review, and conceptual narrative are the primary cues. Yet similar to experimental lab studies, a major counterintuitive (and often misunderstood) modeling insight is that including a few constructs usually yields a more insightful analysis than including every empirically relevant construct. As one modeler told us, "The goal of a model is not to increase the R^2, but to unpack β_1. Models don't contribute by expanding the scope laterally, but by unpacking a causal story." By focusing on a few constructs, the modeler is in effect holding all other factors constant. That is, *excluding* a construct from an analytic model is analogous to *including* it as a control in econometric research or as a selection criterion for theoretical sampling in multi-case theory-building research.

Gambardella et al. (2015) illustrate as follows. The authors ask how delegating decision rights to employees influences firm performance on knowledge-related tasks. Prior research examined the influence of delegation on employee efficiency, but not its influence on employee motivation. To examine delegation, motivation, and firm performance, the authors *exclude* efficiency from their model by assuming that employees are equally efficient, regardless of degree of autonomy. In this way, the authors focus on an underexplored effect of delegation while controlling for the influence of a significant but understood factor (efficiency).

A second construct choice is the abstraction level. Here, a key counterintuitive insight is that models often benefit from defining constructs at a high level rather than using multiple, narrow constructs. For example, Dushnitsky (2010) models when founders disclose their inventions to investors in order to raise money, vs. use a contingent payment scheme. Rather than specifying a complex profit formula including demand and costs, he represents the venture's profits as a single variable π and then examines how π is affected. Contrary to intuition, abstracting constructs (a) focuses attention on the focal relationships, thus, making the model more generalizable, and (b) simplifies the model, thus making it more tractable and transparent.

A third construct choice is how to represent the constructs mathematically, which is distinct from how they are defined theoretically (this is analogous to empirical research, in which constructs have theoretical definitions and empirical measures). Constructs may be represented mathematically in multiple ways, such as categories (e.g., specialists vs. generalists), discrete variables (e.g., number of firms), or continuous variables (e.g., profit). As in empirical research, the theoretical and mathematical definitions should fit, as the value of the model results for broader theory hinges on the link between the two.[11]

3.4.2 | Mathematical relationships

The second setup element is the mathematical relationships among the constructs. Relationships are typically specified by equations that link the constructs to together. They may be derived from prior theory (i.e., workhorse models) or empirical observation. For example, in their model of the Wintel duopoly, Casadesus-Masanell and Yoffie (2007) model demand q as a

[11]With this in mind, a common approach is to initially use a simple mathematical definition for tractability, and then subsequently employ a more realistic definition (and one better matched to theory) in later robustness checks. For example, Hellmann (2007) asks when employees with novel ideas will leave their firms to become entrepreneurs. His initial model represents ideas as having either high *or* low value (a categorical distribution). After conducting the initial analysis, he then revises his model to employ a continuous distribution, and finds that the results still hold.

function of market size α, price p, and buyer utility β. Thus, the equation $q = \alpha\,(1 - p/\beta)$ describes the relationship between these constructs, with price p defined as the sum of Intel's and Microsoft's prices ($p \equiv p_I + p_M$). This suggests that demand will increase in the size of the market and buyer utility, and decrease in price.

3.4.3 | Assumptions

The final element of the setup is the assumptions. Assumptions play two key roles in analytic modeling: they (a) make the analysis tractable, and (b) determine where the results hold. As several experienced modelers told us, understanding the assumptions is particularly valuable for understanding how and why the model produces its results. In fact, one described his shortcut to reading analytic models, "I look at the question, the assumptions, and result." The implication for consumers is to pay particular attention to assumptions.

Jia (2013) illustrate as follows. She uses a biform game (NGT first stage, CGT second stage) to examine when suppliers will invest in relationship-specific assets as a function of (a) value created from doing so, and (b) degree of competition from other suppliers. A key assumption is that contracts that ensure the supplier's ability to capture value *ex post* cannot be formed or enforced. Thus, competition alone determines the division of value between supplier and buyer. The decision to exclude contracts makes the model more tractable by avoiding the need to model variables like enforcement regime. It also means that, while the theoretical insights about the influence of competition on investments are logically valid regardless, the output of the model will be more predictive of (and a better match for) settings where contracts are less relevant.

While many assumptions relate to a specific analytic model (e.g., contracts are not enforceable, in the above), there are several assumptions that are frequently used but not always explicit. These are useful for consumers to understand because they are a source of widespread confusion. One such assumption is *rationality*. In the context of analytic modeling, rationality means that agents objectively calculate the best available action based on their current information. In reality, of course, agents satisfice rather than optimize, have incomplete mental models, and have biases. Yet assuming that agents are rational (and more broadly, that they are cognitively astute) is a potent and often valuable assumption for several reasons.[12]

First, assuming rationality enables the modeler to focus on the incentives and constraints that shape agents' decisions, rather than the biases and other factors that may affect their decisions in real life. Second, assuming rationality reduces the (infinite) universe of *possible* actions and outcomes to a more manageable subset (i.e., those that are likely to occur if agents behave rationally). This can improve the usefulness and generalizability of the analysis in addition to the tractability. Assuming rationality is thus often a good starting point for building theory, in that it provides a benchmark and allows comparison across models.

Another common yet often misunderstood assumption is equilibrium reasoning. Equilibria are frequently viewed with suspicion due to the (incorrect) belief that they imply an

[12]We thank a reviewer for noting the potency of the rationality assumption, and the rich body of research in strategy and economics on the topic (e.g., Gavetti & Levinthal, 2004; Gavetti & Menon, 2016; Levinthal, 2011). This research has yielded "softer" approaches for modeling rationality, for example, subjective rationality (Ryall, 2003) and cognitive hierarchy modeling (Camerer, Ho, & Chong, 2015). These alternatives often offer greater behavioral realism, but impose their own assumptions. Thus, rationality assumptions continue to have widespread use and be helpful.

unchanging environment. They do not. Instead, equilibria are the points at which the model outcomes will not change without external influence. For example, in an NGT model, an equilibrium is the set of actions in which each agent is taking its own best actions given the actions of other agents. Thus, no agent has an incentive to deviate unilaterally.

Equilibrium reasoning is useful because it captures the interaction between agents or forces. That is, rather than just reflecting the effect of *A* on *B*, equilibria reflect the effect of *A* on *B given the effect of B on A*. Moreover, like rationality, equilibrium reasoning prunes the universe of possible outcomes to a more manageable subset. But, it is not without its downsides: equilibria may fail to exist (which has an unclear theoretical interpretation), may be sensitive to changes in model design (Ross, 2018; Ryall, 2003), or, relatedly, may inadvertently fail to capture possible or even likely outcomes (e.g., firms may fail to anticipate rivals' responses to strategic actions; typically this possibility is not reflected in game-theoretic analyses).[13]

Overall, a common misconception is that assumptions make models tractable at the expense of theoretical insight. There is truth to this view: unrealistic assumptions may lead to an unrealistic and uninsightful analysis (Nelson and Winter, 1982; Sutton & Staw, 1995).[14] More broadly, although, assumptions are central to how insights are achieved in that they focus attention on the salient elements of a problem and establish boundary conditions on the resulting insights. Indeed, all research relies on assumptions, although they are often implicit such that their influence (and even existence) may be unclear. Thus, a strength of analytic modeling is that its assumptions and their logical impacts can be both precise and transparent.

3.5 | Model analysis

The analysis identifies the logical implications of the model setup, thus, revealing primary insights of the model. Sometimes this analysis is performed by manipulating the equations of the model to obtain a closed-form solution and/or using proofs to identify and validate propositions. In other cases, or in addition, models may be solved numerically. This entails assigning numeric values to constructs and calculating the resulting outputs. Numeric analysis reduces the need for analytic tractability, and thus often allows less restrictive assumptions to be used. But, it has traditionally been seen as inferior relative to analytic solutions, which are "fully specified" across all construct values and can provide ironclad mathematical proofs (Adner et al., 2009).

A frequent approach is to perform the analysis in stages. That is, much as econometric researchers may present results beginning with controls, then main effects, and then interactions, the modeler often begins with a benchmark (i.e., baseline) model and then adds complexity. For example, Alcácer, Dezsö, and Zhao (Alacer et al., 2015) explore when rival firms collocate in markets by constructing a game-theoretic model of two firms choosing whether to enter a pair of markets. In the benchmark model, neither of the firms learn from prior experience. The authors then extend the model to allow firms to learn from experience gained in a

[13] Ross (2018) provides a rich example using the prisoners' dilemma. In the classic setup, the equilibrium is one in which both agents follow the individually rational strategy of confessing, although it is collectively better not to do so. If however the prisoners can coordinate, or face forces not in the model (e.g., social pressure), the equilibrium might instead be cooperation.

[14] This point was memorably demonstrated by Postrel (1991) who constructs an NGT proof of the "Flaming Trousers Conjecture," which holds that a model exists in which it is optimal for bank presidents to set their pants on fire.

focal market (local learning), and then again to allow firms to apply knowledge gained anywhere (global learning).

Staging limits the complexity introduced at each stage, and thus, clarifies the impact of each change and allows readers (if they wish) to "step through" the logic of the model. A common theme (although not a universal practice) among the modelers we interviewed is that they often ensure that each stage of their own models has a useful insight or intuition. As an experienced modeler told us, "Each intermediate stage must have an intuition!" The implication for consumers is that they gain a faster and better understanding of the results if they explicitly look for and pay attention to the particular insights at each stage.

A second common approach is a comparative statics, in which the modeler identifies an equilibrium outcome(s) and then indicates how changes in one or more parameter values alters the equilibrium outcome of the model. For example, Casadesus-Masanell and Zhu (2010) ask how incumbent firms can best reconfigure their business models to fight low-cost, ad-sponsored rivals. Their analysis identifies several potential equilibrium responses (e.g., ad-sponsored vs. subscription vs. hybrid). They then conduct a comparative static analysis to identify which response is optimal as a function of specific parameter values such as for product quality and consumer preferences. For example, as the entrant's product quality approaches that of the incumbent, the incumbent prefers a pure (subscription or ad-sponsored) model over a hybrid. Like staging, the implication for consumers is that they can gain a better and faster understanding of the results if they focus on each outcome and the conditions under which it occurs.

3.6 | Model validity

A key concern for many consumers is whether the model results are valid. As noted earlier, *internal validity* (i.e., whether the model is logically consistent) is a major strength of the method. Specifically, the "audit trail" left by equations and proofs builds strong internal validity by allowing readers to step through the analysis and ensure that each step flows from the last.

External validity (i.e., whether the model provides accurate insights about the real world) is more challenging. Some theorists argue that, if the assumptions are reasonable and the analysis is correct, then the model ought to have external validity. Here, the emphasis is on the model's logical implications. Many consumers, however, prefer to assess external validity for themselves by (a) building intuition regarding how the insights of the model play out in real settings and (b) assessing whether alternative explanations exist. Both the conceptual narrative and a literature review can help in these tasks. In addition, extensions to the main analysis may be valuable, especially when used to make the model richer or more realistic (e.g., by relaxing assumptions or introducing additional dynamics).

One type of extension is to supplement analytic results with a numeric analysis. Numeric analysis may enable more realistic assumptions (per above), and can improve consumers' intuition. For example, Wu, Wan, and Levinthal (2014) examine how incumbent firms address radical technology change. Through a closed-form analysis, they derive propositions and threshold values that describe when incumbents invest more (or less) in a radical new technology than entrants. They then use a numeric analysis by assigning values to constructs and plotting the resulting relationships among strategy, resources, and market share. These graphs enhance the readers confidence and intuition regarding the model's realism (and external validity).

A second approach is to compare the model results with real-world empirical data. For example, Hagiu and Wright (2015) examine firms' choice to be a reseller (i.e., selling products directly to buyers) vs. a marketplace (i.e., platform to facilitate exchange between buyers and sellers). Their analysis indicates that firms will prefer to be resellers when product demand is high, and will prefer to be marketplaces when product demand is low *or* when third-party firms have valuable information. The authors then compare these analytic results to data on Amazon. Consistent with their analysis, they find (a) Amazon is more likely to be a reseller for popular DVDs and a marketplace for less popular ones, and (b) Amazon often *transitions* from a marketplace to a reseller as cumulative sales in a category grow and it reaches information parity with its marketplace sellers. This empirical analysis enhances the readers' confidence and intuition that the analytic results are realistic and externally valid.[15]

4 | PAIRING ANALYTIC MODELING WITH OTHER METHODS

In the prior two sections, we positioned analytic modeling within the broad repertoire of well-known methods in strategy and organizations and laid out a guide for understanding and appreciating analytic models. In this section, we look forward by pairing analytic models with other prominent methods and emphasizing under-exploited opportunities. In doing so, we illuminate complementarities between methods, and provide insights into how consumers can pair their own preferred methods with analytic modeling in their own research (Table 4).

Verbal theory. Verbal theory is effective for theorizing about novel phenomena, integrating existing theories, and extending them (e.g., Helfat and Peteraf, 2015; Afuah and Tucci, 2012). A primary advantage of verbal theory is that it can flexibly incorporate and relate constructs and ideas from disparate theories or empirical observations. It is also highly accessible to a broad audience and can open the door to fresh empirical research directions. Yet, as we noted earlier, natural language arguments are often less effective for untangling nuanced interactions among constructs like direct and indirect effects. Furthermore, verbal theory may be less adept at identifying precise boundary conditions (e.g., conditions required for a result to hold). Thus, analytic modeling and verbal theory are natural and powerful complements.

A particularly generative pairing is to use verbal theory as a starting point (e.g., to introduce a tension) for an analytic model. The model can then sharpen the internal logic and confirm the insights of the verbal theory. Baldwin and von Hippel (2011) illustrate this blend. They use verbal theory to explore the processes and tensions among alternative modes of innovation (e.g., single firm vs. user community), including contingencies like communication costs. Then, they develop an analytic model to sharpen these comparisons, leading to the provocative claim that user innovation and open collaboration may eventually displace innovation by single firms.

4.1.1. | Multi-case theory building

Analytic modeling pairs particularly well with multi-case theory building and qualitative methods more broadly. Qualitative research methods typically focus on broad questions, and

[15]An important observation, however is that linking model results to real-world observations is not always feasible (e.g., when data are not available), and may not be desirable (e.g., when the model excluded constructs that are either confounded with included constructs or are highly relevant in the real world). Here, however, models may still have external validity to the extent that they can provide insight into the plausible mechanisms and boundary conditions for a given phenomenon. In other words, their results may be valid, even if they are not readily observable.

TABLE 4 Complementary methods for building and testing theory

Description	Questions and Settings	Advantages	Complementarity with Analytic Models
Theory Building Cases			
One or more rich, empirical descriptions of particular instances of a phenomenon, typically drawing on several data sources (Yin, 1994; Eisenhardt, 1989). Multiple cases build theory using a replication logic.	Best for process questions and undertheorized and novel settings. Typically addresses open-ended questions, e.g., how novel phenomena emerge, and how they play out over time.	Rich grounding in empirical data provides discipline for theory building. Often identify novel and unexpected theoretical constructs and relationships. Very accessible to general readers.	Theory building cases can be a rich source of novel yet empirically grounded insights for constructing analytic models Analytic models can sharpen causal mechanisms and identify boundary conditions for emergent theoretical frameworks (e.g., Sarkhartov & Folta, 2014).
Simulation			
Computational representations of a real-world system. Representations are coded into software that is run repeatedly under various experimental conditions in order to produce emergent patterns (Davis et al, 2007; Harrison et al, 2017; Burton and Obel, 2011).	Best for extending simple theory and interaction of multiple processes. Typically addresses the outcome of two or more basic processes that interact, e.g., exploration / exploitation; efficiency / flexibility, especially over time.	Internal logical consistency ensures theoretical rigor. Facilitates experimentation (e. g., adding constructs or altering parameter values) to extend theory. Somewhat accessible to general readers.	Simulation can extend complex analytic models, especially for numerically solved models (e.g., Posen et al, 2013). Analytic models can unpack causal mechanisms and internal logic of simulation results (e.g., Davis et al, 2009).
Verbal Theory			
Natural language arguments to explain a phenomenon (Freese, 1980).	Best for synthesizing and extending prior work. Powerful for broaching new ideas. Often used to generate predictions for subsequent empirical testing.	Requires little apparatus and can address a wide range of phenomena. Very accessible to general readers.	Verbal theory can generalize analytic modeling theory such as by relaxing assumptions. Analytic models can sharpen the internal logic of verbal theories and identify boundary conditions (e.g., Baldwin & von Hippel, 2011).
Econometric Analysis			
Statistical analysis of large-scale quantitative datasets in order to disconfirm hypotheses (Angrist & Pischke, 2009). Increasingly used for open-ended investigation of phenomena.	Best for identifying the existence and magnitude of effects in a dataset, often to test predictions based on prior theory Typically addresses whether and to what extent hypothesized relationships are supported in a sample	Data ground analysis, allowing estimation of real-world effects and interactions. Large sample sizes may allow robust identification and generalizable results	Analytic models can develop precise constructs, logic, and predictions Econometrics can test predictions of analytic models (e.g., Lieberman et al, 2018; Luo et al, 2018; Berry & Kaul, 2015).

often yield surprising insights about novel phenomena and new domains (Eisenhardt et al., 2016). Among these methods, multi-case theory building is particularly explicit about its theory development goal (Gehman et al., 2018). Yet, the theoretical frameworks that emerge (from this and other qualitative methods as well) are often broad-brush, with imprecise mechanisms and under-specified boundary conditions.

Analytic modeling complements multi-case theory building because it can provide theoretical precision, particularly in untangling causal mechanisms and sharpening boundary conditions. For example, Galunic and Eisenhardt (2001) use multi-case theory building to explore the intriguing “charter change” process that fueled Omni's extraordinary multi-decade leadership of the global technology sector. Charter change is a process for continually realigning business units with evolving global markets. Helfat and Eisenhardt (2004) then used Omni to ground their novel verbal theory of “resource redeployment,” in which corporations benefit from redeploying resources across business units over time. Finally, Sakhartov and Folta (2014) use this verbal theory as their inspiration for an analytic model. Their model unpacks the conditions under which resource redeployment is effective, and disentangles it from the (empirically confounded) effects of resource synergies. As this illustrates, the two methods complement one another: cases provide a rich source of novel phenomena and theoretical insights (as well as potential conceptual narratives), while analytic models can weave these insights into theory in a precise and rigorous way.

4.1.2. | Simulation

Analytic modeling and simulation (i.e., computational modeling) are similar in their reliance on formal representations to develop and extend theory. Yet, the two methods are not the same. As noted earlier, they differ in their technical setup and analysis, and generally offer distinct contributions to theory-building. Simulation modelers typically build or extend theory by running experiments (e.g., using different parameter values) (Burton & Obel, 2011). Relative to analytic models, this makes simulations adept at exploring what patterns emerge from the interaction of multiple constructs, especially over time. In contrast, analytic models are often better able to indicate why these patterns emerge and when (i.e., under what conditions) they hold. Thus, again, the two methods are powerful complements.

Davis et al. (2009) illustrate as follows. The authors first develop a simulation to examine the relationship between organizational structure and performance under different market conditions. They experiment with four market dimensions to explore the environmental drivers of this relationship. Among other insights, they find an intriguing “edge of chaos” in which semi-structures (e.g., simple rules) outperform both unstructured (very flexible) and highly structured (very efficient) arrangements in highly unpredictable markets. The authors then build an analytic model to unpack (a) the precise shape of the structure-performance relationship (i.e., skewed inverted V) that emerged from the simulation, and reveal (b) its underlying mechanism (i.e., high error rate when flexibly improvising in highly unpredictable markets). This causal mechanism was difficult to identify without the clarity of an analytic model.

4.1.3. | Econometric analysis

Analytic models also complement quantitative empirical methods such as econometric analysis. Relative to econometric research, analytic modeling gives researchers more control (e.g., correlation among variables can be avoided, data availability is not relevant), precision (e.g., mechanisms are mathematically verifiable), and transparency (e.g., audit trail of equations and proofs). Yet without data, analytic models can only develop theory about what *might* be. In contrast, econometric methods can reveal what *is*.

An increasingly common pairing is thus to use an analytic model to develop precise theoretical predictions and relevant constructs for later econometric testing. For example, Wu (2013) uses data from the cardiovascular medical device industry to test predictions on complementary assets from an earlier analytic model (Levinthal & Wu, 2010). Similarly, Berry and Kaul (2015), Ethiraj et al (Ethiraj, 2007), Kaul and Wu (2015), and Lieberman et al. (2018) use analytic models to develop hypotheses, and later test them. While these authors could have relied on verbal theory, analytic modeling made their hypotheses more precise and falsifiable (Montgomery et al., 1989).

4.2 | The future of analytic modeling

Finally, what might be the future of analytic modeling? As the field enters the age of "big data," a method based on long-hand math is not an obvious candidate for growth. Even qualitative research has seen benefits from software for coding data and automating transcription. In contrast, analytic modeling remains firmly rooted in the pre-digital age. Thus, one might wonder if it will be "crowded out" by other methods.

We think this will not occur for several reasons. First, analytic modeling brings unique value to theory building, and is thus an effective complement to other theory-building methods, both in individual studies and across the field broadly. Analytic models will for example continue to have value in simplifying verbal theory to its essence, adding precision and deeper insights to theory-building case studies, and unpacking the internal mechanics of simulations. Moreover, analytic models are also likely to be useful complements to emerging quantitative theory-building methods that exploit big data like machine learning, which excels at identifying patterns but lacks causal mechanisms (Gandomi & Haider, 2015; Tidhar & Eisenhardt, 2020).

A second reason for optimism is the wealth of opportunities for advancing the methodological state of the art. For example, strategy scholars are now building theory using options-pricing models that are solved numerically (e.g., Posen, Leiblein, & Chen, 2018; Sakhartov, 2018), while powerful closed-form approaches exist in the finance literature that have yet to be adopted in strategy (e.g., Heston, 1993; Kou & Wang, 2004). These approaches may allow new research questions to be asked, and existing questions to be addressed in greater depth. Useful concepts already introduced may gain influence as well. For example, self-confirming equilibria and subjective rationality (Ryall, 2003), strategic mental models (Menon and Yao, 2017), and cognitive hierarchy modeling (Camerer et al., 2015) may all reflect strategic and organizational settings more richly than the rationality and equilibrium reasoning often employed.

Overall, there are both numerous opportunities for pairing complementary current methods with analytic modeling as well as generative new pairings. And, their use becomes more likely as potential consumers of modeling (i.e., non-modelers) develop a better understanding of and appreciation for analytic modeling and its relevance for their own research.

5 | CONCLUSION

We began by noting that analytic modeling is valuable for theory development. Moreover, the number of scholars trained in the method and the sophistication of the approaches used seems to be growing. Yet, achieving the full benefit of this promising trajectory requires bridging the information gap between producers and consumers of modeling research. Our aim has been to address this gap by contributing a guide for reading and understanding analytic models and using their results. We also position analytic modeling within the broad repertoire of theory-building methods, and explore valuable pairings with complementary methods. In sum, our aim is to enhance the usefulness of analytic models by making them more accessible and compelling to the broad scholarly community.

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APPENDIX: CITATION ANALYSIS

In order to understand the usage of different research methods in the strategy and organizations literature, we surveyed all articles published from 2005 to 2019 in *Academy of Management Journal*, *Academy of Management Review*, *Administrative Science Quarterly*, *Strategic Management Journal*, *Organization Science*, and *Research Policy*. *Management Science* was also included, but only articles published the relevant departments (business strategy, entrepreneurship, organizations, technological innovation, R&D, and product development) were retained. Using Web of Science, we obtained the title, author(s), year, volume, issue, and abstract for each. We excluded editorials and book reviews.

We then identified the primary research method of each article as belonging to one of the following categories: *econometric (archival*, *experimental*, *survey)*, *qualitative*, *analytic model*, *simulation model*, or *other (verbal theory*, *reviews*, and *methods)*. We did so by searching the abstracts for keywords relevant to each of the methods (e.g., game theory or formal model). An initial list of keywords was generated manually and was refined throughout the coding process. For the abstracts that did not contain relevant keywords, we read each abstract. When the necessary, we examined the article content directly.

Our original analysis spanned 2005–2015. We subsequently extended our data to 2019 which yielded a sample of 6,966 articles, of which 279 (4%) were analytic models, 902 (12.9%) were qualitative, 4,577 (65.7%) were econometric, including archival, survey, and experimental studies, 110 (1.6%) were simulations, and 1,098 (15.8%) were methods papers, reviews, or verbal theory.[16] Using only the 2005–2015 papers, Web of Science citation counts for the original analysis revealed mean citation counts for analytic models to be 20.6, qualitative 37.2, econometric 34.5, simulation 21.6, and reviews/other 68.4.

We conducted additional analysis in order to understand the source of these differences. Our primary dependent variable of interest was *citations received*, operationalized as a count of total citations as listed on Web of Science. Our focal independent variable *primary method* was operationalized as binary variables representing each of the following categories; analytic model (omitted), quantitative, qualitative, simulation, and theory/review. We also included several controls. To account for *author status*, we collected data on the rankings of the universities with which each author was affiliated at the time of publication. Specifically, we took the average of the 2016 University of Texas at Dallas Top 100 Business School Research Rankings for the affiliations of the first three authors of each paper and created a reverse-coded “author status” variable. We controlled for *time* by including dummy codes for articles' year of publication. *Publication outlet* was accounted for using journal-specific dummy variables.

Because the outcome interest was a count variable, we implemented a negative binomial regression approach to estimate the influence of our predictor variables. This was chosen over a Poisson model because a likelihood-ratio test comparing the two models was significant ($p < .01$), indicating that the citation counts are over-dispersed.

Overall, we find that analytic modeling papers receive significantly fewer citations than other those using other methods, *even when controlling for publication year*, *outlet*, *and author status*: the binary indicators for qualitative, quantitative, or theory and review papers were all

[16]Ghemawat and Cassiman (2007), observe that the use of game theory in strategy increased from one article every seven journal years in 1975–1994 to one every three journal years between 1995 and 2004. We consider a broader range of analytic modeling approaches and find mixed evidence of the same: over the 2005–2015 period, analytic models accounted for 3.5% of publications, vs. 5.2% from 2015 to 2019.

highly significant ($p < .01$). No significant difference in citation count between analytic and simulation models was revealed. A closer look at the findings, and the indicate rate ratios (IRR) in particular, reveals the magnitude of these effects: relative to analytic modeling, the likelihood of receiving citations increases by 89% for qualitative methods and by 62% if the paper is quantitative.