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Simplification errors in predictive models

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Abstract

Organizational and political responses to strategic surprises such as the credit crunch in 2008 and the pandemic in 2020 are increasingly reliant on scientific insights. As a result, the accuracy of scientific models has become more critical, and models have become more complex to capture the real-world phenomena as best as they can. So much, so that appeals for simplification are beginning to surface. But unfortunately, simplification has its issues. Too simple models are so generic that they no longer accurately describe or predict real-world cause-effect relationships. On the other hand, too complex models are hard to generalize. Somewhere on the continuum between too simple and too complex lies the optimal model. In this article, the authors contribute to the ongoing discussion on model complexity by presenting a logical and systematic framework of simplification issues that may occur during the conceptualization and operationalization of variables, relationships, and model contexts. The framework was developed with the help of two cases, one from foresight, a relatively young discipline, and the other from the established discipline of innovation diffusion. Both disciplines have a widely accepted foundational predictive model that could use another look. The shared errors informed the simplification framework. The framework can help social scientists to detect possible oversimplification issues in literature reviews and inform their choices for either in- or decreases in model complexity.

KEYWORDS

complex causal models, foresight, innovation diffusion, innovativeness, oversimplification, weak signals

1 | INTRODUCTION

Predictive models are a balancing act between a valid representation of complex real-world phenomena and well-focused research by isolating (parts or dimensions of) phenomena. Unfortunately, despite the rigor applied to model development, focus and isolation can lead subsequent research into an implicit downward spiral towards severe oversimplification.

Individual studies develop models on the shoulders of their predecessors, but sometimes lose sight of the older model variants' contextual limitations or incomparable operationalizations. At the level of overarching theory, a string of small, justifiable simplifications can lead to myopia, confusion, and, at its worst, wrong notions. The social sciences exhibit several examples of such oversimplification strings, and two of them underpin the theoretical simplification framework detailed in this paper. Both cases deal with real-world foresight: the first looks at strategic intelligence in the shape of weak (paradigm unrelated) signals, and the second at strategic insight into the adoption of innovations.

Since the mid 20th century, policymakers have turned to science for insights into and solutions for societal challenges. In our century, governmental and organizational responses to climate changes, the pandemic, or the invasion of Ukraine made the direct links between science and politics all the more visible. Such direct links emphasize the significance of the real-world validity of research and, thus, the significance of avoiding oversimplification. The simplification framework can be seen as an urgent and relevant step in addressing problems with real-world validity.

The framework took a basic or foundational model to develop a catalog of simplification steps. The basic model presents the relationship in which one phenomenon affects another. It distinguishes between a variable representing a phenomenon acting as a cause, a variable representing a phenomenon acting as an effect, a link between variables representing the effect from one phenomenon on the other, and the context in which the model applies (see Figure 1).

Such models represent a foundational component in efforts to explain and predict phenomena. Phenomenon 1 as represented by variable V1 can thus be used to explain or predict phenomenon 2 as represented by variable V2. But such models can also simplify real-world complexity in its three components: phenomena, relationships, and context.

Firstly, single or few dimensionally defined variables may in reality represent multi-dimensional phenomena. In cases of over-simplification, the reduction of dimensions is too severe and unintentionally hides significant dimensions, incompleteness, or overlap of dimensions.

Secondly, when a relationship between phenomena is modeled as a one-sided linear effect, the actual relationship may be two-sided, involve multiple relationships between different dimensions of phenomena, or be nonlinear. Oversimplified relationships can unintentionally hide significant facets of a much more complicated relationship from view.

Finally, if models are presented in splendid isolation, the actual issue under study may be contingent on contextual conditions not included in the representation. When oversimplified, isolated models omit significant information like moderating and mediating variables, joint causes, multiple consequences, and limitations that emerge from different contexts.

The balance between real-world complexity and model focus is settled during the conceptualization, operationalization, and validation stages. Each stage is completed with academic rigor. In scientific research, our shared methods to arrive at models are careful, conscientious, and covered with explicit model limitations and caveats. In addition, the rigorous methodological rules give us the confidence to select and combine model parts to induce our model. We strive for elegance: to find the most straightforward model that accurately depicts deep insights and is uncomplicated to test. Peer review does a final check on the quality of decisions made. Nevertheless, individual acts at the level of conceptualization and operationalization of phenomena, relationships, and contexts can, over time, still lead to a model unable to reveal the insights we seek, despite passing validation tests.

In the next section, we will briefly discuss the ongoing discussions about the optimal complexity of models and explain our choice to develop the framework for two distinct cases (Section 2). The first case is from the research domain of managerial foresight. The second example is from the domain of innovation diffusion. Both domains work hard to develop predictive models as a decision-making means. In Section 3, the two cases are discussed per framework component (phenomenon, relationship, and context) and stage (conceptualization and operationalization). In Section 4, the cases' issues were inductively extrapolated into a framework (Section 4, Table 2). Conclusion and discussion are in Section 5.

2 | BACKGROUND

The need for a simplification framework emerged from the ongoing discussion about model complexity. Supporters and opponents of complex models try to find the optimal level of complexity that makes a model easy to understand yet still accurate and informative about the underlying real-world phenomenon. For example, a very complex model may merely inform on one, highly context-specific situation, while a straightforward model may not be accurate enough to explain and predict any real-world phenomenon (Del Giudice, 2021; Perkins & Grotzer, 2005). In other words, both overcomplicating and oversimplifying models have tradeoffs, and the solution is finding the optimal level of complexity to minimize both tradeoffs. The optimal level sits between the upper extreme of individual models for each situation or innovation and the lower extreme of the broad,

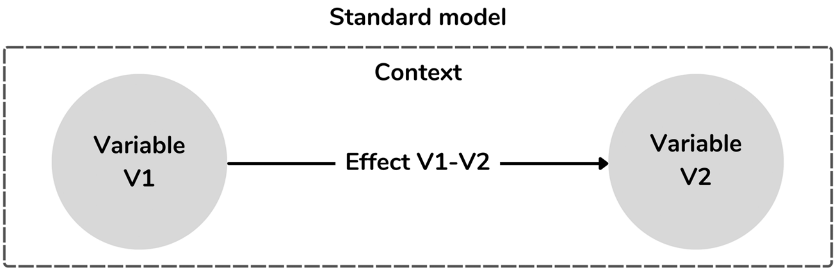

FIGURE 1 A model of phenomenon 1 serving as a cause (represented by variable V1), phenomenon 2 serving as an effect (represented by variable V2), and the effect from phenomenon 1 on phenomenon 2 (represented by relationship V1-V2).

untestable general law and gravitates around the combination that still refers to real world phenomena but can be quantitatively tested.

Problems with modeling have been explored for many types of advanced models like longitudinal growth models (Bliese & Ployhart, 2002), structural equation models (Landis et al., 2000), or models with multiple mediation paths (Taylor et al., 2008), to the point that appeals to reduce model complexity are appearing (Saylors & Trafimow, 2021; Schoenenberger et al., 2017). Unfortunately, insights on avoiding oversimplification are difficult to find. Primarily, insights draw attention to specific types of oversimplification, like the lack of explicating model boundaries (Busse et al., 2017) or problems with integrating mediation and moderation effects (Hayes, 2012; MacKinnon, 2011). A generic framework of issues could have tactical value as a useful checklist for researchers and practitioners using, or developing models to be conscious of potentially misleading simplifications or complications. Therefore, we aim to bring a coherent perspective on simplification issues to contribute to the discussion of optimal model complexity and to provide indicators that warn against errors at the oversimplification end of the balance between oversimplification and overcomplication.

The current thinking on oversimplification in scientific literature is severely fragmented and disjointed. Therefore, we chose to develop a framework inductively. Following the seminal work of Eisenhardt and Graebner on using cases for theory building (Eisenhardt & Graebner, 2007; Eisenhardt, 1989), we chose to explore two diametrical cases.

We selected two case studies from two distinct disciplines that can be seen as different in field maturity, yet both include a broadly accepted two-variable model. Using an established and nascent discipline reduced the likelihood that the classification emerged as a side effect of either maturity level. Using broadly accepted models may help readers follow our inductive logic. Using the most basic model of two variables and their relationship allowed for more straightforward problem exploration. Results can then serve as a reference for exploring more complex models.

The first case describes modeling problems in weak signals (weak signals are paradigm unrelated strategic information) from the domain of strategic foresight. The second case describes modeling problems of the innovativeness phenomenon from the field of innovation diffusion. These cases represent the opposite poles of research domains. Strategic foresight is a relatively young domain with fluid paradigms that are hardly separated from its multidisciplinary origins. Innovation diffusion is a mature, clearly demarcated domain with fixed paradigms. Nevertheless, analysis of the cases resulted in the emergence of the same issues, suggesting that these were generalizable across organizational and managerial research disciplines.

The domain of strategic foresight aims to find robust ways to predict changes in the organizational environment and their impacts on organizations. One of its research lines focuses on detecting the earliest signals of a change. As a change emerges in the organizational environment, it emanates signals in the shape of ambiguous, incomplete, and sometimes (partly) erroneous information. In the eyes of outsiders, such signals are weak because they are more or less unrelated to their paradigms and thus difficult to detect and interpret.

One of the first studies on the phenomenon was done by Ansoff (1975), who also coined the term "weak signal" (Ansoff, 1975, p. 23). He described the relationship between the emergence of a change and the progression of knowledge of that change within strategic planning processes (Ansoff, 1979). Weak signals would become less weak over time, as more becomes known about the change, until it is perfectly understood. At that point the signal was called strong.

The idea still stands and has been enriched with research into methods to elicit weak signals (Thorleuchter & Van den Poel, 2015; Yoon, 2012), barriers to signal detection and interpretation (Ilmola & Kuusi, 2006; Lesca et al., 2012), ways to increase the accuracy of signal interpretation (Kaivo-oja, 2012; van Veen et al., 2019), and the link between signal interpretation and organizational behaviors and performance (Battistella, 2014; Rohrbeck & Kum, 2018).

Although this theory is seen as the foundation of modern research into strategic foresight and planning (Holopainen & Toivonen, 2012), there is a lack of consensus about the phenomenon it describes (van Veen et al., 2021). One of the models describing the effects of weak signals is the relationship between signal weakness and interpretation speed (see Figure 2). Imaginably, this effect is different for the various explanations of weakness, which range from vague pressures that loom but cannot be enacted (King, 1984) to knowledge in the shape of threats or opportunities that can be enacted right away (Schoemaker & Day, 2009).

The lack of consensus on the conceptualization and operationalization of the weak signal phenomenon not only leads to first-order problems like confusing results but also to second-order problems for both foresight academics and practitioners. Lack of consensus emerges from the abundance of weak signal definitions (Rossel, 2011). Definitions no longer always refer to the same phenomenon, which hinders the combining of findings into new

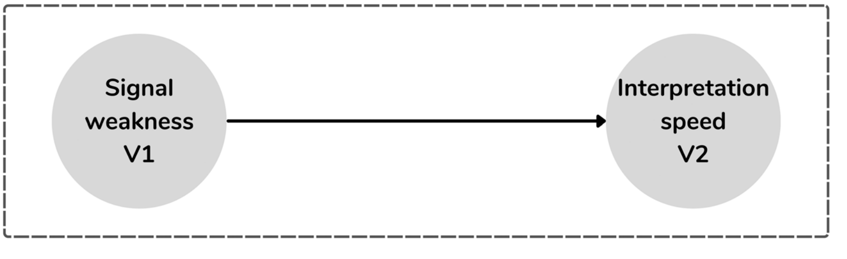

FIGURE 2 A positive linear relationship between weak signals (cause) and the effect of weakness on interpretation speed.

theory (van Veen et al., 2021). We see two problems emerge from that point:

Firstly, when academics and practitioners use insights and methods from academic research to make sense of weak signals, they should be able to rely on insight and method soundness. Unfortunately, the lack of consensus and thus of validation means that they have no way of checking that soundness. Therefore, they have no way of knowing if there are blind spots to overcome in the identification of weak signals and how to do that effectively and efficiently. There is excellent work done by Rohrbeck and Kum (2018) that shows that firms who match foresight efforts to the level of uncertainty in their environments outperform, and when firms oversimplify or overcomplicate, they underperform. These findings imply that a correct conceptualization and operationalization of weak signals is crucial for competent foresight research and practices.

Secondly, when academics build on Ansoff's theory on strategic surprises, they should be able to rely on and build with results that reflect real-world phenomena. Oversimplification limits that. For example, most research on weak signals does not discriminate between weakness levels like Ansoff did, which led to a bias that favors medium level weakness. We do not know if our insights in managing strategic surprises are true for severely weak signals.

Hence, with all respect for the efforts in the nascent field of foresight and the rolling insight that goes hand in hand with the maturing of the field, considerations for oversimplification should be part of its instrumentarium.

Now our attention turns to the mature domain of innovation diffusion. In contrast to the work on weak signals, innovation diffusion is an old and well-established scientific domain. Ideas about diffusion as a social phenomenon were formulated by the sociologist Tarde in the 19th century for example (see Kinnunen, 1996). Initially, in the first half of the 20th century, different disciplines separately worked on diffusion research without knowing each other and thus different traditions in terms of variables and models emerged (Katz et al., 1963). Later, in the second half of the 20th century, a multi-disciplinary theory of diffusion of innovations was developed. One of the central authors of this theory is Rogers, who first published the theory in 1962. His book, “Diffusion of Innovations,” soon became the norm for innovation diffusion researchers and practitioners alike (Rogers, 1983). Diffusion of innovations became a comprehensive theory involving different levels of analysis and different parts that fit together. The theory involves a macro level studying the diffusion of an innovation in society, a meso level focusing on subsequent groups of customers (adopters) and a micro level studying the adoption process followed by individuals. Each level involves multiple models. On the individual level, for example, the stages in the process of adoption by individuals were studied (Ettlie, 1980) and criteria by which potential adopters can evaluate innovations (e.g., Ostlund, 1973, 1974). All the models on different levels of analysis combine and thereby form one of the most established and comprehensive theories in social science. The adoption processes of individuals add up to form diffusion in groups, which in turn add up, forming a diffusion curve, and hence the levels fit together. Yet, even in this domain simplifications emerged that impair validity. These simplifications can be partly traced back to the origins of the domain.

Rogers was a graduate student of Ryan and Gross, two agricultural sociologists, who initiated a basic part of the diffusion model already in the 1940s (Ryan & Gross, 1943). Their work was to explore the diffusion of a particular case in a specific context: the diffusion of hybrid corn in the 1930s in the USA. Upon closer inspection, it also seems that the context in which hybrid corn diffused was very specific and hardly generalizable to the context of radical innovations in general. Hybrid corn was dominant in price/performance (radical innovations seldom are dominant from the beginning onwards), the potential adopters, farmers, were well-known (potential adopters of radical innovations are often hardly known), and the innovation could be tried by farmers on a limited basis each year (while other innovations suffer from a legacy and unmet infrastructural and institutional requirements that make them difficult to try on a limited basis). These conditions were meticulously described by Ryan and Gross (1943). We conclude that the context that shaped the initial model was more of an exception rather than widely generalizable to radical innovations.

The adoption of the innovation hybrid corn by farmers refers to research explaining diffusion almost exclusively in terms of demand-side phenomena, which is understandable because that was the bottleneck at that time. The demand-side phenomena were further narrowed down by focusing on the characteristics of potential adopters. The focus allowed diffusion scholars to separate innovators, early adopters, early majority, late majority, and use these subgroups to explain the emergence of the diffusion curve (Ryan & Gross, 1943). Hence a subdomain emerged in diffusion research that focuses on the characteristics of subsequent groups of adopters of an innovation, aiming to find what characteristics set innovative individuals apart (e.g., the ones adopting an innovation relatively early) (See Dedehayir et al., 2017). This was highly relevant from a practitioner's perspective because predicting the first groups of adopters for a radically new innovation is a difficult step (e.g., Tauber, 1975).

So, over time, a simplified model of the original comprehensive and well-founded theory of diffusion of innovations became popular. In this model the innovativeness of individuals is assessed in terms of their characteristics, and this innovativeness in turn is used to predict (the timing of) adoption of an innovation by individuals with these characteristics (see Figure 3).

This model formed the basis for hundreds of research projects, all over the world, exploring characteristics of individuals adopting innovations (for an old overview see Engel et al., 1990; for a more recent overview see Dedehayir et al., 2017).

Figure 3 is straightforward but hides much confusion on what defines the innovativeness of individuals, how to measure it, and how context-specific the model is. Many different definitions and operationalizations of the variables “innovativeness of individuals” do exist. Innovativeness of individuals is sometimes measured in terms of a psychological scale, in practice referring to a set of 5-point or 7-point items in a questionnaire. Many different scales can be

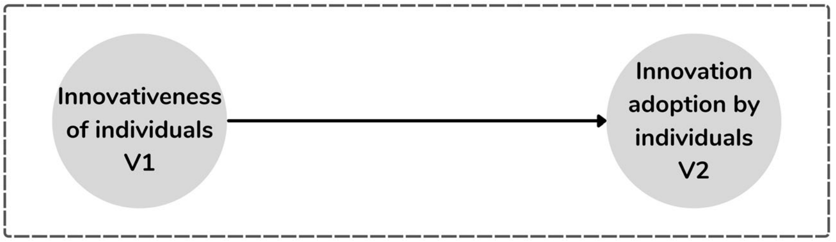

FIGURE 3 "Innovativeness of individuals" (represented by variable V1) affects (relationship V1-V2) the adoption of innovations (represented by variable V2).

distinguished (Bearden et al., 2011). Innovativeness is sometimes inferred from specific personal characteristics, like level of education, age, and so on. Adoption is often defined and assessed as "buying." Although, even for that fairly straightforward variable, different definitions and operationalizations exist (Damanpour & Schneider, 2006). Some see adoption as "buying," others see adoption as "implementation" or "putting into practice."

Engel et al. (1990, p. 709–712) provide a comprehensive overview of all relevant studies exploring which independent variables describing (potential) customer characteristics relate to early adoption. Per variable the number of studies supporting a relationship between that variable and early adoption is tabulated. The percentage of a relationship varies a lot indicating a rather weak relationship.

In short, the weak signal model and the innovation diffusion model are generally accepted and serve as a foundation for overarching theories. Closer analysis will reveal the oversimplification within these models and how that could lead to errors in theory (see Section 3).

Both models represent cause-effect relationships between (sets of) variables representing a real-world phenomenon. The models have one variable causing an effect on one other variable, claimed to occur independently from the model context (Wright, 1921). Variables, relationships, and context are three essential model components, and each one can be simplified. Simplification becomes oversimplification when the model no longer represents the real-world phenomenon it refers to.

Furthermore, simplification can occur in two stages: model conceptualization and operationalization. Conceptualization refers to how phenomena, relationships, and contexts are represented and defined in a model with variables and effect relationships. Operationalization describes how the variables and their effects are measured and assessed empirically. Oversimplification can stem from both overly simple definitions and measurements.

The following section will discuss the two cases per framework component (variable, relationship, and context) and stage (conceptualization and operationalization).

3 | TWO CASES INFORMING THE FRAMEWORK OF MODEL SIMPLIFICATION

Table 1 presents the main conclusions on the challenges associated with each component and phase of the cases' models. It starts with the conceptualization and operationalization of variables that depict the phenomenon (rows 1 and 2), proceeds to the relationships among variables (rows 3 and 4), and concludes with the context of the model (row 5).

It could be argued that a model is at its most advanced state when it represents a universal law. The collective studies on context specific models are supposed to bring it closer to universality. Model refinements, limitations, moderating and modifying variables are the scientist's tools to advance models to universal validity.

In the two cases, one on weak signals from the relatively young discipline of strategic foresight, and the other on innovativeness from the established discipline of innovation diffusion, a broadly accepted two-variable model appeared to be rife with problems of oversimplification.

In the conceptualization of weak signals and innovativeness, the factors describing the phenomenon are not easy to disentangle, let alone isolate. Despite conceptual unclarity, the definitions are incredibly focused to assist academic study, and in these two cases that resulted in at best inconsistent definitions.

Moreover, the operationalization of these concepts often fails to capture the real-world phenomenon. The dynamic, continuous nature of weakness is reduced to a static dichotomous variable, that obscures the nonlinearity of the phenomenon. Measuring innovativeness post hoc could also point to the mere act of adoption of an innovation rather than an innate trait, and co-occurring operationalizations like education level can obscure actual effects of innovativeness more than enlighten it when their effects depend on innovation type.

In both cases, the oversimplifications of variables and relationships has led to confusing and contradictory results, while individual studies passed statistical tests and other validation challenges. In the field of innovativeness, the tendency to oversimplify the characteristics of innovators and the adoption process resulted in weak and non-generalizable research findings.

For weak signals, subsequent studies do not account for the contextual differences of the phenomenon, but it is quite imaginable that studying the weak signals of emerging financial crises differs from those precursing a pandemic. In innovativeness, disregarding contextual sectors like, for instance, supply, demand, or guiding institutions is likely to incur considerable blind spots and provides reasonable doubts about the level to which results of different studies can be combined and compared.

TABLE 1 Main conclusions on oversimplifications in the cases weak signals and innovativeness.

	Weak signal	Innovativeness
		
Phenomenon conceptualization	The phenomenon "weak signal" has been captured in at least 60 definitions that partly overlap, but the overlapping factors vary broadly (van Veen et al., 2021), which indicates conceptual confusion.	A conceptualization issue is that the "innovativeness" phenomenon is seen sometimes as an innate trait, but logic dictates that it can only be innate if the trait is not product-category specific. However, the same individual can adopt one innovation and disregard or reject another, so the phenomenon is more complex and found to be product-category-specific (Dedehayir et al., 2017; Engel et al., 1990).
Variable operationalization	Despite the accepted notion of weakness as a dynamic and continuous phenomenon, variables representing weak signals are foremost dichotomous and static (Ilmola & Kuusi, 2006; Schwarz et al., 2014).	Product-category specific innovativeness is often seen as a multi-dimensional construct yet the dimensions vary widely and so does the operationalization (Bearden et al., 2011).
Relationship conceptualization	The accepted linear relationship between weak signals and interpretation or search characterizations was upended by a study using different levels of weakness (van Veen, 2020).	Considerable research effort to distinguish statistical relationships between consumer characteristics (representing individuals' innovativeness) and early product adoption only led to weak and hardly generalizable results. This may be caused by oversimplifications during relationship conceptualization. The mechanisms by which product category-specific innovativeness have an effect on adoption are hardly unraveled (Dedehayir et al., 2017).
Relationship operationalization	Study results pointing towards a linear relationship between weak signals and i.e. search or interpretation passed statistical tests and were validated by later studies, which indicates that oversimplification can remain obscured despite academic rigor (van Veen, 2020).	A lack of conceptualization of the relationship between innovativeness and adoption has its consequences for operationalization of the relationship. If product category-specific "innovativeness" is measured in terms of its consequence i.e., innovation adoption, then the relationship is altogether ignored.
Context	Research on weak signals gets triggered by system shocks and the wish to anticipate the next one as soon as possible. These shocks differ from natural disasters to political, economic, and societal discontinuities. Although the phenomenon under study always disregards the shock and concentrates on how we can anticipate new shocks early, it cannot be ruled out that a shock's domain influences the model we study.	Contextual phenomena play an important role in adoption and diffusion processes. It is interesting to see that fast diffusion requires conditions to be optimal in the entire market system: on the supply side, the demand side, and the guiding institutions in a context where the supply- and demand-side actors operate. Focusing on the demand-side and neglecting all supply-side and other contextual variables makes the results of innovation diffusion research incomparable to contexts that are different from the initial context in which the model was described (Dedehayir et al., 2017).

4 | SIMPLIFICATION FRAMEWORK

Individual studies are steps in the scientific journey towards more profound knowledge and theory building. Model simplification in one step can lead to issues when left unchecked in the next step. After several of those unchecked steps, our shared knowledge and theory suffer from severe oversimplification and thus diminishes in quality and functionality. A framework describing when, where in the model and how much oversimplification has occurred can help researchers check their work more efficiently for this problem.

Table 2 gives a helpful overview of simplification issues in three ways. Firstly, by reading the table from left to right, researchers can check new models for oversimplification per model component, stage, and captured complexity level (Section 4.1). Secondly, by reading the table from right to left, researchers can detect possible oversimplification in existing models by its symptoms in literature reviews (Section 4.2). Finally, reading column 3, researchers can determine their model's complexity level. By plotting a model in column 3, researchers can deliberately decide if the chosen level does justice to the real-world situation the model represents or if model complexity should move up or down one or more levels (Section 4.3).

4.1 | Checking new models for oversimplification

Reading Table 2, columns 1–3, from left to right, researchers can check new models for oversimplification per model component, stage, and captured complexity level.

TABLE 2 Classification of issues in model oversimplification.

Component	Stage	Issues in increasing levels of model complexity	Symptoms in literature
Phenomena *Choices about how to represent a phenomenon with variables: variable development and measurement*. Please find examples in sections 3.1. and 3.2.	**Conceptualization** Are different (subsets of) dimensions required to describe the phenomenon accurately?	1. The phenomenon can be described with an obvious one-dimensional variable. 2. The phenomenon should be expressed in multiple dimensions but is conceptualized as one-dimensional. 3. Phenomenon intricacy should result in multiple overlapping variables but is conceptualized in one variable. 4. The phenomenon should be comprised of multiple partly overlapping multi-dimensional variables.	Direct indicator: • An abundance of definitions emerges in the literature. Definitions cannot easily be combined. • Different variable names are proposed for the same phenomenon. • Different conceptualizations are proposed for the same variable. • Different disciplines focus on different dimensions of a phenomenon, raising validation concerns. Indirect indicator: • Review articles ask for conceptual clarity in defining phenomena.
	Operationalization Are different items required to measure a phenomenon accurately?	1. A single one-dimensional scale suffices. 2. A multi-dimensional scale is required to capture different phenomenal aspects, but a one-dimensional scale is used instead. 3. The variables should be measured with multiple overlapping (linked) scales to account for the underlying phenomenon's entire behavior. 4. The variables should be measured with multiple overlapping (linked) multi-dimensional scales to account for the underlying phenomenon's entire behavior: The measurement affects relationships that can be assessed empirically, e.g., a binary variable can never lead to a curvilinear relationship.	Direct indicator: • Many different ways to measure the phenomenon emerge in the literature (even for similar conceptualizations). • The scaling of the variable does not reflect the levels in the phenomenon. • The operationalization of the variable is mixed up with consequences of the variable or with co-evolving aspects of it. Indirect indicator: • Review articles ask for consistency in measuring variables.
Relationship *Choices about how variables affect each other: relationship direction and linearity*. Please find examples in sections 3.3. and 3.4.	**Conceptualization** Can different relationships be hypothesized between the same phenomena in terms of direction and or linearity?	1. A single one-directional linear relationship suffices. 2. Different dimensions can lead to varying relationships in terms of direction and or linearity. 3. The direction of a relationship (cause-effect) is mis-specified, for example, two-sided versus one-sided causality, covariation versus causality. 4. Multiple relationships are responsible for the behavior of related phenomena in different ways.	Direct indicator: • Different disciplines build up their models around the same phenomenon. Indirect indicators • Siloed disciplinary perspectives and review articles ask for interdisciplinary collaboration.
	Operationalization Are different statistics required to reveal the true nature of	1. The method is accurate. 2. The method assumes a particular type of relationship,	Direct indicator: • Within the same discipline, empirical results regarding the

(Continues)

TABLE 2 (Continued)

Component	Stage	Issues in increasing levels of model complexity	Symptoms in literature
	relationships in terms of direction and or linearity?	for example, some correlation measures assume a linear relationship. 3. The method assumes that outlier removal will improve accuracy, yet outliers describe essential behaviors. 4. The method assumes singular relationships instead of a system of relationships.	same relationship yield different results. • Meta-analysis in one discipline assesses inconsistent results.
Model Context *Choices about the interaction between a model and its context: model heterogeneity and dynamism.* Please find examples in sections 3.5. and 3.6.	**Conceptualization** Are different variables influencing the relationship (e.g., moderators, mediators, or joint causes) required to keep a model accurate?	1. The model represents a universal law. 2. The heterogeneity of the context is simplified. Hence, relevant variables are omitted, and conditionality remains implicit. 3. Dynamic relationships between variables or models are expressed as static. Hence, the model represents one instance of an interactive model. 4. The effect of the variable time is ignored while intrinsic to the phenomenon. Hence, emerging effects remain implicit as well as temporal limits to model validity.	Direct indicator: • Different disciplines build up their models around the same phenomenon. Indirect indicators • Siloed disciplinary perspectives and review articles ask for interdisciplinary collaboration.
	Operationalization Are different ways to measure or isolate variables and to compensate or deal with their effect required to reveal the actual behavior of the phenomena?	1. The model can be measured independently from its context. 2. An integrated measurement should reflect the effect of contextual variables on the primary relationship between phenomena. 3. A holistic measurement should reflect that the starting point of reasoning determines what cause is and what effect. 4. An infinite measurement should reflect how a model changes over time.	Direct indicator: • Within the same discipline, empirical results regarding the same relationship yield different results. • Meta-analysis in one discipline assesses inconsistent results. • Context is made up of different variables in each research project. Indirect indicators • Per discipline, context is operationalized differently.

Note: The conceptualization and operationalization issues in assessing the context's relationship and effect can hardly be separated. They can originate from conceptual and operational issues regarding the phenomena.

Table 2 separates models into three components in which simplification can occur. Firstly, complexities in the model phenomena (row 1), secondly in the relationship between phenomena (row 2), and finally in the model context (row 3). Issues can occur during two stages: model conceptualization and operationalization (column 2). Oversimplification (or overcomplication) occurs when the complexity captured by a model does not match real-world complexity close enough to remain a valid representation (column 3).

Conceptualization refers to how phenomena, relationships, and contexts are represented and defined in a model with variables and effect relationships. Operationalization describes how the variables and their effects are measured and assessed empirically. Oversimplification can stem from overly simple definitions and measurements.

We distinguish four levels of decreasing model simplicity. The first level describes simple, elegant models. The second level describes the models that have to incorporate more variables or dimensions to remain valid. The third level describes the models that acknowledge the interference of multiple overlapping variables or models for it to remain accurate. Finally, the fourth level describes the intricate models that accommodate systems of multi-dimensional models to remain valid over time. Oversimplification occurs when a given model should incorporate a higher level of complexity to remain valid.

4.1.1 | Types of phenomenal oversimplification

When a one-dimensional variable represents a multi-dimensional phenomenon, special attention must be given to the original cloud of variables. When it is difficult to isolate a variable because natural or other obvious logic is lacking, chances are that oversimplification occurs.

For example, a one-dimensional choice may lack significant dimensions, or multiple variables may behave as dimensions of one variable. In both cases, dimensions determining the phenomenon remain hidden. That can become a validation problem when findings on a phenomenon are combined into a body of knowledge. For example, if studies looked at a partial phenomenon and these parts did not entirely overlap, one could question the validity of the findings.

4.1.2 | Types of relationship oversimplification

When variable dimensions remain hidden, the relationship with other variables suffers. For example, relationships may be modeled to show a singular linear behavior, which hides significant findings. Curvelinearity or other hidden aspects of relationships may surface when these relationships are multifaceted or aggregated for multiple dimensions. This, too, can become a problem in the validation of findings.

4.1.3 | Types of contextual oversimplification

When contextual phenomena influencing a model receive a mere mention as model limitations, special attention must be given to all research using that model. If limitations were not accounted for in each repetition, significant information has been omitted, and findings may become misleading.

Although Table 2 cannot be seen as a complete and finite overview of issues, applying the table to the cases in Section 3 suggests that it can serve as a detection tool. Using the table will help sensitize researchers to oversimplification issues and help them to make deliberate, explicit choices about their models. Describing these choices in their papers will help reduce oversimplification in shared theories and bodies of knowledge.

In the next section, we will apply the table to a model's provenance: the underpinning theoretical or empirical models from literature.

4.2 | Checking underpinning models for oversimplification

Reading Table 2 from right to left, researchers can detect possible oversimplification in existing models by the symptoms that emerge from literature reviews.

Table 2 lists symptoms from literature and separates them into direct and indirect symptoms. Direct symptoms are the actual references to an abundance of ways to define or measure the same phenomenon, confusing results, or meta-analyses. Indirect symptoms are appeals for clarity or collaboration within or between disciplines.

4.2.1 | Symptoms of phenomenal oversimplification

When definitions or measures of a phenomenon have been oversimplified, studies will likely differ in the chosen dimensions for representing said phenomenon. The differentiation in definitions and measures is a byproduct of the difference in the focus of empirical studies on (parts or aspects of) a phenomenon in isolation. Studies build on one another to fill knowledge gaps, and thus foci change slightly. At the individual study level, the choices resulting from focus are logical and grounded in previous research. However, at the overarching level, definitions and measures may -at a certain point- no longer represent the same phenomenon or phenomenal dimension. At that point, any subsequent study should be very careful with the grounding of its model in underpinning literature. Before grounding can take place in those cases, earlier definitions and measures should be analyzed to reveal a possible significant lack of overlap.

A large number of definitions of a particular phenomenon as a fraction of all the articles on that phenomenon directly indicates the coexistence of significantly different definitions. Review articles requesting clarity and unification are an indirect indicator of phenomenal oversimplification.

A multitude of conceptualizations can occur between and within disciplines. The same phenomenon can have multiple names, conceptualizations, and operationalizations between disciplines. Within disciplines, a phenomenon can be conceptualized and operationalized with somewhat arbitrary or overlapping dimensions. Multidisciplinarity is not a symptom of oversimplification, but when paired with inconsistent results, oversimplification is a plausible cause.

In Section 3, we demonstrated that many alternative definitions of individuals' innovativeness have co-existed for decades. For signal weakness, we showed that over 60 different conceptualizations emerged since the term's coinage in 1975. In both cases, this led to oversimplification issues.

4.2.2 | Symptoms of relationship oversimplification

The second set of symptoms revolves around the relationship in focus. The type and form of the relationship can be mis-specified. For example, a cause-and-effect relationship assumes a one-way relationship from the cause to the effect, yet other types of relationships are also possible.

When phenomena consist of multiple dimensions, but research focuses on different singular dimensions, then inconsistent results regarding their measurement and relationships are expected. A literature review showing confusing results is a red flag for oversimplification.

Researchers are inclined to simplify phenomenal intricacies so that their variables focus on phenomena' main characteristics and behaviors without distorting the assessment of the relationships between phenomena. This simplification is, almost inevitably, a function of the context and timeframe in which researchers operate. Since researchers explore similar relationships between phenomena in different contexts and timeframes, the inconsistency of their results is inevitable.

4.2.3 | Symptoms of model contextual oversimplification

A final set of symptoms revolves around the context in which the relationship between the phenomena is assessed. The context may include other phenomena affecting the cause-and-effect relationship.

In the example of innovativeness, we have shown how the context and timeframe of research on innovation diffusion have caused particular simplifications. The first authors, Ryan and Gross, meticulously described the context and timeframe in which they formulated their innovation diffusion model: US farmers adopting hybrid corn around 1940 (Ryan & Gross, 1943).

Moreover, the simplifications researchers adopt are a function of their research's goal. Their goal determines the perspective from which they observe the phenomena, relationship, and context and the level of analysis they choose. Therefore, simplifications will vary widely because goals and researchers' perspectives vary. For example, economic theories serve varying purposes, like explaining unemployment and inflation as well as innovativeness in a country. The goal is for researchers to emphasize particular phenomena and discard other phenomena; hence, economic theories conceptualize and operationalize a country entirely differently. An example of varying perspectives is provided by differences between models of innovation in an industry seen from a government's or a company's perspective.

Checking findings from a systematic literature review for oversimplification symptoms may prompt researchers to dig deeper by reading the table from right to left. If a symptom mentioned in Table 1, column 4 surfaces, columns 1-3 may shed light on where, when, and how much oversimplification occurred in individual studies. A deeper insight into its causes can help researchers find ways, logically or empirically, to reconcile the phenomenal, relationship, or contextual differences at the individual level instead of adding to the confusion at the overarching level.

In the next section, we will apply the table to possible up- or downgrades of model complexity.

4.3 | Checking underpinning models for oversimplification

Reading Table 2, column 3, researchers can determine the level of complexity in model components and stages and deliberately decide if the chosen level does justice to the real-world situation the components represent.

When symptoms of oversimplification occur, the first step is to reflect on the extent of captured complexity in model components.

To manage oversimplification, researchers must be aware that a continuous progression of complexity exists. Real-world complexity ranges from none to infinite, and its existence can remain unseen to wholly understood. Hence, models can vary significantly in the extent of complexity captured in the model components.

To manage oversimplification, we have aggregated component complexity into model complexity, as shown in Table 3. We distinguish four levels of captured complexity. A "clear model" is presented in the first level, containing two obvious one-dimensional variables. One variable has a linear effect on the other, independent of context. In the fourth level, a "cryptic model" is presented in which multiple overlapping and multi-dimensional variables have chaotic relationships in a fuzzy context.

Levels of intricacies differ in the detailing a model requires to keep resembling the real-world problem it tries to replicate. The determinism of the correct level in the case of a particular research project is done through comparison with the description of the intricacies per category per level.

Mere complexity does not cause symptoms of oversimplification. As long as complexity can be unraveled in parts that are observed the same way by researchers across disciplines and over time, these symptoms do not emerge. On the other hand, if these symptoms are pervasive or persistent, likely, oversimplification issues are too.

Table 3 suggests that models can be categorized in levels of captured complexity and that moving up or down between levels can help researchers find a complexity sweet spot. The sweet spot refers to the lowest level of captured complexity to represent a real-world phenomenon and still significantly overlaps with earlier studies for building theory and knowledge.

5 | CONCLUSION AND DISCUSSION

In the social sciences, models capture the behavior of social phenomena in the most spartan form. Real-world complexity and dynamism may be reduced to two variables and their hypothetical relationship and then tested for hypothesis accuracy. It is precisely this reduction that allows us to do controllable and falsifiable research. We strive for the simplest accurate version possible, the most elegant model. Rigorous procedures bind reduction to avoid mistakes and misinterpretation. However, logical

TABLE 3 Levels of model complexity

	Component	Level of Captured Complexity			
		Level 1	**Level 2**	**Level 3**	**Level 4**
Determinism	*Model*	Clear Model	Complex Model	Clouded Model	Cryptic Model
					
	Phenomena	Obvious variables	Multidimensional variables	Multiple overlapping variables	Multiple multi-dimensional overlapping variables
	Relationships	One-directional linear relationship	Multifaceted one-directional relationship	Bidirectional curvilinear relationships	Chaotic relationships
	Context	Context independent	Integrated contextual variables	Dynamic system of models	Fuzzy model or system

choices at the level of individual studies may lead to severe oversimplification errors at the discipline level. In turn, literature reviews unchecked for oversimplification errors can lead to misguided choices in subsequent studies.

We developed a simplification framework to assist researchers in checking their modeling in three ways. Firstly, researchers can check new models for possible oversimplification in model components, stages of development, and captured complexity. Secondly, researchers can check existing models for oversimplification by looking for direct and indirect references to its symptoms in literature reviews. Thirdly, researchers can locate the simplification/complexity sweet spot: the lowest level of captured complexity while the model still represents the real-world phenomenon and remains integrated into earlier conceptualizations.

We began exploring the problem of oversimplification with the most basic model: that of two variables and their relationship. The issues found for the basic model can then serve as a reference for exploring more complex models, which may or may not suffer from the same oversimplification. We used cases from two disciplines of social sciences that can be seen as opposites in field maturity but similar in their focus on prediction. Each case consisted of a broadly accepted two-variable model. Analysis of the cases resulted in the emergence of the same issues, suggesting that these were generalizable across organizational and managerial research disciplines.

Further anecdotal evidence for this assumption was found in the handbook of marketing scales by Bruner, (2012). Almost all phenomena are conceptualized in slightly different versions. One of the most striking examples is the concept "attitude of individuals," for which 65 different scales or operationalizations are presented.

5.1 | Signals of possible oversimplifications within domains

We discussed the effects on subsequent research if oversimplification is uncorrected for the three model components. For instance, when phenomenal intricacies remain unaddressed, the need to redefine persists. Literature reviews will include studies and reviews that refer to the many definitions and appeal to phenomenal clarity. Such appeals could serve as an indicator that uncorrected intricacies are an issue. When relationship intricacies remain unaddressed, confusing or conflicting results can surface, or the gap between findings and the real-world situation remains challenging to bridge. A domain's combined gap analyses can serve as an indicator of such intricacies. Finally, when contextual intricacies remain unaddressed, models can become established without their caveats and result in a house-of-cards body of knowledge that surfaces with model refinements. The abundance of these effects in extant literature emphasizes how persistent and pervasive oversimplifications are.

5.1.1 | Effects of unaddressed oversimplifications

When phenomenal oversimplifications, indicated by a growing lack of common definitions and operationalizations, are left unattended, validation of findings could become a problem. When conceptualizations and operationalizations partially overlap across the studies that researchers are building upon, they must clarify whether their reasoning is based on the overlap or not. When tens of definitions exist, statistical analysis of the distance between definition aspects should replace logical deduction. When such an analysis does not happen, studies lack construct validity.

More complex relationships like curvilinearity can remain hidden when construct validity is an issue. If this is left unattended, studies lack internal and predictive validity. When contextual oversimplification is an issue, models have been separated from significant inherent conditions and can keep moderating and mediating variables hidden. If that is left unattended, studies lack external validity. When the findings of studies lacking in validity are used for new studies (as opposed to repetitive studies to check validity), a domain's body of knowledge and theory building are in danger, and progress is shaky at best.

5.1.2 | Suggestions to address oversimplifications

It seems evident that researchers pay more attention to indicators like definition abundance, confusing or conflicting results, persistent gaps between findings and real-world situations, or serial model refinement. However, oversimplification will not always surface despite our attention to indicators. In the case of signal weakness, only phenomenal oversimplification was noted but left to exist because every subsequent study created its definition from literature and logical deduction. The dichotomous character of the variables representing weak signals suppressed relationship and contextual complexity, and decades went by without any confusing or conflicting results surfacing. We, therefore, suggest that researchers, whenever they find indications of oversimplification, resort to statistical analysis to let complexities surface instead of moving to the next logical simplification. A systematic way to make such complexity visible for variable definitions is provided by van Veen et al. (2021).

5.1.3 | Future research avenues

We have already hinted at several avenues of future research. Firstly, our assumption that the two cases represent a persistent and pervasive problem involving many other relationships in the social sciences should receive an empirical basis.

Secondly, the interrelatedness of the conceptualization and operationalization of phenomena, their relationships, and model contexts in simple models should be clarified further. Findings will help establish if hidden complexity should be solved at the category, conceptual, or operational levels or just for specific combinations. It will also illuminate which statistical methods are preferable.

Thirdly, more complex models can be checked for oversimplification and its effects. More complex models could suffer more due to the addition of phenomena, variables, and relationships. However, more complex models could also suffer less because they have already captured more complexity. Only research will tell us how more intricate models relate to the simple model discussed here.

Fourthly, our list of issues is by no means finished. For example, we did not include the oversimplification issues that can occur when a relationship is conceptualized at certain levels of analysis. We suspect many decisions in a study's set-up can lead to oversimplification, but further research should clarify if an exhaustive list is possible or necessary.

Fifthly, research into overcomplication, the other end of the balance, could bring new perspectives on the optimal level of complication. Saylors and Trafimow argue that while oversimplification of models may not perfectly account for reality, the complexity of reality does not necessarily require equally complex theories. They highlight that the simplicity of a theory, like Newtonian theory in physics, can still be effective despite not being a literal description of reality. In contrast, they caution against the increasing complexity of models in organizational research, which can lead to a decrease in the joint probability of a model being true. We share the notion that the optimal model strikes a balance, and hypothesize that research on both ends of the balance combined may lead to clarification of what optimal means (Del Giudice, 2021; Saylors & Trafimow, 2021).

Finally, a method could be developed to help mitigate hidden oversimplification and its effects. At this point, we assume that normative models can benefit from an explorative check. For instance, a statistical exploration of possible variables could let a competent variable surface from data without a natural or apparent logical definition. Similarly, combining statistical and logical data could let more complex models appear. In both cases, variables and their relationships would suffer less from the implicit oversimplifications inherited from earlier findings. Establishing the value of an explorative phase preceding a normative study is also an excellent first step in future research.

To conclude, we frankly admit to being no better than the simplified examples we discussed.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request. A summary of data generated or analyzed during this study is included in this published article and its supplementary information files. Full data are available from the corresponding author upon reasonable request.

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