IMPROVING THE MARRIAGE OF MODELING AND THEORY FOR ACCURATE FORECASTS OF OUTCOMES

Edited by Arch G. Woodside

ADVANCES IN BUSINESS MARKETING & PURCHASING

VOLUME 25

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United Kingdom – North America – Japan
India – Malaysia – China

Emerald Publishing Limited
Howard House, Wagon Lane, Bingley BD16 1WA, UK

First edition 2018

British Library Cataloguing in Publication Data
A catalogue record for this book is available from the British Library

ISBN: 978-1-78635-122-7 (Print)
ISBN: 978-1-78635-121-0 (Online)
ISBN: 978-1-78714-891-8 (Epub)

ISSN: 1069-0964 (Series)

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CONTENTS

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PREFACE

Fiss (2007) and Meyer, Tsui, and Hinings (1993) suggest that many of the problems in empirical research on organizational configurations derive from a mismatch between methods and theory. Configurational theory suggests a clean break with the predominant linear paradigm. Rather than implying singular causation and linear relationships, a configurational approach assumes complex causality and nonlinear relationships where "variables found to be causally related in one configuration may be unrelated or even inversely related in another" (Meyer et al., 1993, p. 117). The linear paradigm relies on null hypothesis significance test (NHST) – proposing alternative hypotheses that directional relationships exist (e.g., increases in variable X associates with increases in variably Y).

Are Fiss (2007) and Meyer et al. (1993) correct? If they are correct, why do almost all empirical studies that report forecasting models rely on using symmetric tests (e.g., correlation, multiple regression analysis (MRA), and structural equation modeling (SEM)) and reporting NHST findings? If such analytical tools as symmetric tests and NHST represent bad science, what alternative data analytical tools should researchers use? This volume in *Advances in Business Marketing & Purchasing* answers these questions and provides examples of using configurational modeling that are somewhat precise outcome tests (SPOTs). The volume in your hands or on your screen suggests that you stop using NHST and symmetric tests such as correlation, MRA, and SEM. The chapters in this volume describe complexity theory tenets and provide examples mostly from the business-to-business strategy, marketing, and purchasing literatures on why and how to build asymmetric models using configurations of antecedent conditions.

Yes, Fiss (2007) and Meyer et al. (1993) are correct on all counts. Additional researchers (Armstrong, 2012; Gigerenzer, 1991; Hubbard, 2016; Ziliak & McCloskey, 2008) – who have carefully reviewed and documented research tools on the usefulness of data analytic methods – reach the same or similar conclusions. Using symmetric tests such as correlation analysis, MRA, and SEM misrepresents the information quality and quantity that a researcher can mine from a data set. Usually the decision by researchers to use symmetric tools and NHST is done automatically, without explicit thinking about the availability and usefulness of asymmetric tools and SPOT. Most researchers propose theories in strategic management, finance, organizational behavior, marketing, and management at the case level but then do symmetric tests on the basis of relationships among variables. Offering case theory and doing variable-relationship testing is the mismatch that Fiss (2007) and Meyer et al. (1993) identify. Both the construction and testing of theory at the case level using asymmetric tests of configurational casual statements is possible and several examples are available (e.g., Frösén, Luoma, Jaakkola, Tikkanen, & Aspara, 2016; McClelland, 1998; Ordanini, Parasuraman, & Rubera, 2014; Wu, Yeh, Huan, & Woodside, 2014).

The dominant practice in the teen years of the 21st century in constructing forecasting models relating to strategic management is to perform MRA and SEM and test resulting models for fit of the predictions of the observations for a dependent variable. However, "Achieving a good fit to observations does not necessarily mean we have found a good model, and choosing the model with the best fit is likely to result in poor predictions. Despite this, Roberts and Pashler (2000) estimated that, in psychology alone, the number of articles relying on a good fit as the only indication of a good model runs into the thousands" (Gigerenzer & Brighton, 2009, p. 118). These studies are examples of shallow analysis that are accurately describable as examples of the rubbish that saddens McCloskey (2002).

The editor-in-chief of at least one journal, *Basic and Applied Social Psychology*, has now banned the practice of reporting NHST findings as well as confidence intervals from future articles accepted for publication. The NHST and confidence intervals ban announcement by Trafimow and Marks (2015) confirms Hubbard's (2016) and Ziliak and McCloskey's troublemaker status in attempting to overthrow bad with good science. This action exemplifies Gigerenzer's (2004, p. 604) call for courage, "To stop the [NHST] ritual, we also need more guts and nerves. We need some pounds of courage to cease playing along in this embarrassing game. This may cause friction with editors and colleagues, but it will in the end help them to enter the dawn of statistical thinking." NHST and fit testing-only of regression models are the pervasive practices in articles appearing in all elite and otherwise ranked journals in management and marketing today. As Hubbard (2016) documented, such corrupt theory construction and testing has dominated these literature streams since the early 1960s. Gigerenzer (2008, p. 170) explained that these practices are procedures of bad science, "Statistical packages allow every difference, interaction, or correlation against chance to be tested." They automatically deliver ratings of "significance" in terms of stars, double stars, and triple stars, encouraging the bad after-the-fact habit. The general problem Feynman (1998) addressed is known as overfitting. Fitting a model to data that is already obtained is not sound hypothesis testing, even if the resulting explained variance, or R^2, is impressive. The reason is that one does not know how much noise one has fitted, and the more adjustable parameters one has, the more noise one can fit. Psychologists habitually fit rather than predict, and rarely test a model on new data, such as by cross-validation (Roberts & Pashler, 2000). Fitting per se has the same problems as storytelling after the fact, which leads to a "hindsight bias (Hoffrage, Hertwig, & Gigerenzer, 2000)."

Symmetric testing of statistical significance of directional hypotheses is pervasive in the literature of business marketing and purchasing. Unfortunately, the evidence is abundant that the dominant logic of symmetric testing of directional hypothesis is bad practice and contributes to bad science. Symmetric tests include correlation analysis, the *F*-test, MRA, and SEM. Researchers perform symmetric tests in most instances with the hope of rejecting null hypotheses. The null hypotheses is a prediction that the relationship between two variables (*X* and *Y*) is statistically equal to zero or that the behavior of firms or customers in group A versus group B have beliefs, attitude, and behaviors equal to zero. Tools for symmetric testing appearing in most articles in today's leading scholarly journals of finance, management, marketing, and psychology include computing correlations (*r*'s) and *b* coefficients in multiple regression analyses. The NHST examines whether or not an observed *r* or *b* coefficient differs from zero to such an extent that the observed difference is unlikely to have occurred by chance alone ($p < .05$ or $p < .01$). The $p < .05$ indicates that the observed finding would occur less than five times in one hundred if the analysis was done 100 times using the same data collection instruments on separate samples.

Critics of the use of NHSTs describe the severe limitations of NHST. One criticism is that all observed findings in NHST differ statistically different from zero if the sample of cases is very large ($n > 5{,}000$). Second, the study of which variables are statistically different from zero and which variable measurements do not differ from zero does not provide information on which configurations of conditions are present that indicate the consistent occurrence of a specific outcome. The primary research focus needs to be on identifying the configurations of ingredients that accurately and consistently predict high performance (or low performance). In reading the chapters in the present ABMP volume, the reader learns how to construct theories of complex configurations of conditions that are sufficient in identifying specific outcomes consistently. "Consistently" refers to the model accurately predicting the same outcome frequently with few, if any, false positives, when testing the model on cases from new samples. Note in reading that a trade-off occurs between accuracy and coverage. Models highly accurate (prediction odds 10 correct to 1 incorrect cases) in forecasting specific cases usually has a greater number of conditions than the accuracy of a simpler model (i.e., a complex statement includes only three conditions that achieves an accuracy of four to one correct to mistaken case identifications). The hope is that the reader reaching the final sentence of this preface is intrigued sufficiently to read the first chapter and then the rest of the volume. Good reading!

Arch G. Woodside
Editor

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EMBRACING THE PARADIGM SHIFT FROM VARIABLE-BASED TO CASE-BASED MODELING

Arch G. Woodside

ABSTRACT

Currently, most of the empirical management, marketing, and psychology articles in the leading journals in these disciplines are examples of bad science practice. Bad science practice includes mismatching case (actor) focused theory and variable-data analysis with null hypothesis significance tests (NHST) of directional predictions (i.e., symmetric models proposing increases in each of several independent X*'s associates with increases in a dependent* Y*). Good science includes matching case-focused theory with case-focused data analytic tools and using somewhat precise outcome tests (SPOT) of asymmetric models. Good science practice achieves requisite variety necessary for deep explanation, description, and accurate prediction. Based on a thorough review of relevant literature,* Hubbard (2016) *concludes that reporting NHST results (e.g., an observed standardized partial regression betas for* X*'s differ from zero or that two means differ from zero) are examples of corrupt research.* Hubbard (2017) *expresses disappointment over the tepid response to his book. The pervasive teaching and use of NHST is one ingredient explaining the indifference, "I can't change just because it's [NHST] wrong." The fear of submission rejection is another reason for rejecting asymmetric modeling and SPOT. Reporting findings from both bad*

Improving the Marriage of Modeling and Theory for Accurate Forecasts of Outcomes
Advances in Business Marketing & Purchasing, Volume 25, 1–18

ISSN: 1069-0964/doi:10.1108/S1069-096420180000025003

and good science practices may be necessary until asymmetric modeling and SPOT receive wider acceptance than held presently.

Keywords: Asymmetric; NHST; SPOT; regression; research; SEM; symmetric

INTRODUCTION: GAINING PERSPECTIVE ON PERVASIVE BAD SCIENCE PRACTICE

Hubbard (2016, pp. 194–198) reviews 41 "overt criticisms of the worth of null hypothesis significance testing (NHST)." These criticisms include Hunter's (1997) call for banning the practice, "Needed: a ban on the significance test." The editor-in-chief of *Basic and Applied Social Psychology* has done just that:

> The Basic and Applied Social Psychology (BASP) 2014 Editorial emphasized that the null hypothesis significance testing procedure (NHSTP) is invalid, and thus authors would be not required to perform it (Trafimow, 2014). However, to allow authors a grace period, the Editorial stopped short of actually banning the NHSTP. The purpose of the present Editorial is to announce that the grace period is over. From now on, BASP is banning the NHSTP. (Trafimow & Marks, 2015)

While Hubbard (2016) and Trafimow and Marks (2015) provide details and convincing evidence that the use of NHST is bad science practice, Tukey (1991, p. 100) provides the obvious (but still shocking) conclusion, "All we know about the world teaches us that the effects of A and B are always different – in some decimal place – for any A and B. Thus, asking, 'Are the effects different?' is foolish."

Following this introduction, the next section of this chapter documents details in the literature supporting the paradigm shift from variable-based to case-based model construction and testing. The section "Why Bad Science Practices Pervade Empirical Management and Social Science" describes the "the forces of inertia" (Huff, Huff, & Barr, 2001) and barriers causing the slow adoption process of modeling precise outcomes and discarding NHST. The section "Visualizing Bad versus Good Science Practices" includes visuals of the causal configurations of antecedents supporting the current pervasive use of bad versus good science practice in empirical sub-disciplines of business and the behavioral sciences (e.g., finance, management, marketing, psychology, and tourism/hospitality research). The section "Principles of Good Science Practice that Are Usually Missing in Most Articles" describes core principles of good science practices appearing in a few articles, but still infrequently, in journals in these literatures. To stimulate the shift from using corrupt research practices to good science practices, this section briefly compares the use of bad and good science practices with the same data set in two articles. After recognizing the opportunity, for researchers seeking to leave behind the shallow waters of NHST and other corrupt research practices and dive deeply into achieving requisite variety via asymmetric theory construction and modeling, the last section concludes with the suggestion to read a few selections from the literature on good science practices.

Weick (2007, p. 16) provides a useful introduction on the need to achieve requisite variety that is relevant for recognizing the need to embrace complexity theory and case-based modeling,

> The importance of a head full of theories is that this increases requisite variety. By that I mean that it takes a complicated sensing device to register a complicated set of events. And a large number of theories can be a complex sensing device if believing is seeing. Haberstroh (1965, p. 1176) describes the law of requisite variety this way: 'If the environment can disturb a system in a wide variety of ways, then effective control requires a regulator that can sense these disturbances and intervene with a commensurately large repertory of responses.' Thus, it takes richness to grasp richness.

The current dominant logic of reporting one-to-five or so regression models in symmetric tests is too simplistic of an approach to the rich tapestry inside most data files. While parsimony is a worthy objective in data analysis, nearly all symmetric tests are overly simplistic.

DOCUMENTING THE REASONS FOR EMBRACING THE PARADIGM SHIFT FROM VARIABLE-BASED TO CASE-BASED MODELING

This section describes the configuration of conditions supporting the rejection of good science practices that include statistical sameness testing (somewhat precise outcome testing, SPOT) and additional good science practices (e.g., model construction that recognizes and attempts to explain/predict anomalies). Fig. 1 illustrates the configuration of rejection conditions and the conditions of good science practices rarely appearing in practice.

Hubbard (2016, p. 9) offers substantial convincing evidence supporting his conclusion that NHST is a corrupt research, "In a nutshell, this book demonstrates that the significant difference paradigm is philosophically suspect, methodologically impaired, and statistically broken." Demonstrating that "… a difference between two means is not precisely zero, or that a correlation between to variables is not precisely zero, are trivial findings" (Cohen, 1994, p. 1000). Hubbard (2016, pp. 192–193) points out that empirical management and behavior science (EMBS) researchers can do better, "In principle, there is no reason why theories in the management and social science cannot yield precise (o interval) predictions … This line of thinking flies in the face of conventional wisdom that theories in these areas are unable to specific point predictions." Though NHST analytics (*r*, multiple regression analysis, MRA,

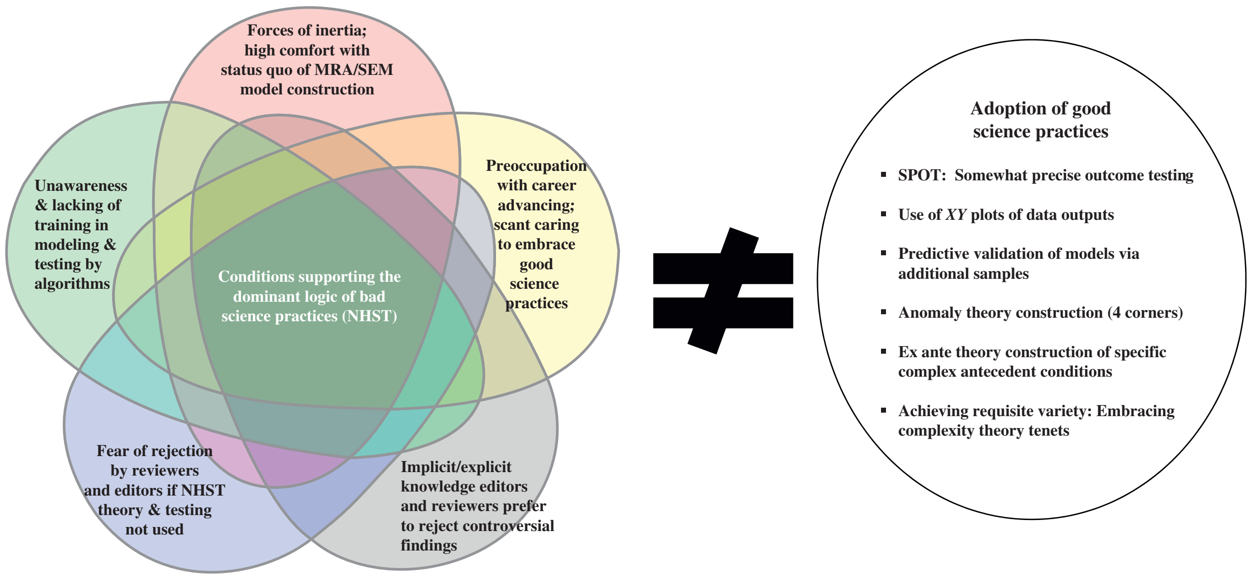

Fig. 1. Forces of Inertia and Barriers Preventing Shifting from Bad ("Corrupt Research," NHST) to Good Science (SPOT).

structural equation modeling (SEM)) dominate across recent decades, studies that include point prediction analytics are available in the relevant EMBS literatures (e.g., Gigerenzer, 1991; Gigerenzer & Brighton, 2009; McClelland, 1998; Montgomery, 1975; Morgenroth, 1964). A core point here is that precise predictions are bounded inside contexts – the idea that the natural sciences, physics included, deal with phenomena that are not context dependent is a myth (Holtzman, 1986, p. 348; Hubbard, 2016, p. 82). Context dependence of precise predictions follows also from Simon's (1990, p. 1) scissors metaphor, "Human rational behavior is shaped by a scissors whose blades are the structure of task environments and the computational capabilities of the actor." For useful model construction, given that the shaping of precise outcomes by two forces – task environment (context) and actor capabilities and backgrounds – is the first axiom, the second axiom is that accomplishing accurate predictions of precise outcomes requires identifying configurations that include combinations of the context and actor features. Granting that including a combination of several context–actor features restricts the range of generalization does not negate the conclusions that researchers can estimate precise outcomes accurately and that testing the accuracy of alternative configurations and with additional features and reductions in the number of features are steps toward generalizing models of precise outcomes.

Somewhat hidden in this discussion of shifting from NHST directional predictions to predicting precise outcomes is the inherent shifting from early discussions in case-based research to writing variable-based hypothesis and examining the existence of relationships via analytics using continuous variable data. Followed at the end of most articles using the dominant logic of variable-based, NHST, to a shift back to presenting implications at the case-based level. Fiss (2007, p. 1181) tellingly describes this three-step awkward shifting,

> But while theoretical discussions of configurational theory thus stress nonlinearity, synergistic effects, and equifinality, empirical research has so far largely drawn on econometric methods that by their very nature tend to imply linearity, additive effects, and unifinality. This mismatch has caused a number of problems. For example, the classic [still dominant] linear regression model treats variables as competing in explaining variation in outcomes rather than showing how variables combine to create outcomes. By focusing on the relative importance of rival variables, a correlational approach has difficulty treating cases as configurations and examining combinations of variables. This becomes particularly evident in the fact that regression analysis focuses on the unique contribution of a variable while holding constant the values of all other variables in the equation.

Fiss (2007, p. 2007) concludes

> Set-theoretic [case-based] approaches are particularly adept at identifying localized effects. Rather than estimating the relative importance of different strategies across all cases, set-theoretic methods allow us to better examine which strategies make sense for which kinds of firm. By contextualizing effects, it becomes easier to go beyond global and typically vague statements about effects, and the identification of different paths rather than a single path offers more opportunities for policy intervention. (Ragin & Fiss, 2007)

The currently dominant paradigm stance asks if an XY relationship is significantly different from zero. The latter and new paradigm asks, what configurations (i.e., screens) of conditions lead to a given outcome, for example, forecasting stock price growth by 10% plus for firms in industry X in the top quintile across each of five financial/marketing metrics (bottom quintile on price/equity ratio, top quintile on sales recent year sales growth, top quintile on customer satisfaction, and so on) is case-based model approach – using a configurational screen rather than a variable-based regression analysis. Case-based predictive modeling is applying asymmetric tests using Boolean algebra; variable-based predictive modeling is applying symmetric tests using matrix algebra. While heretofore unrecognized as a substantial change, the shifts from using symmetric, variable-based tests via regression analysis to asymmetric, case-based tests using algorithms (i.e., screens) by Montgomery (1975) and McClelland (1998) are earthquakes. Both Montgomery (1975) and McClelland (1998) described their use of both symmetric and asymmetric tests; the resulting meager amount of useful information from symmetric tests was their rationale for reporting findings for case-based asymmetric tests. Thus, without their stating the fact, Montgomery (1975) and McClelland (1998) shifted from using corrupt research tools and bad science practices to using honest research tools and good science practices. Subsequently, years later, additional studies include both paradigms with examples of the same shift from the dominant variable-based to the new case-based prediction paradigm in different EMBS contexts (Ferguson, Megehee, & Woodside, 2017; Frösén, Luoma, Jaakkola, Tikkanen, & Aspara, 2016; Ordanini, Parasuraman, & Rubera, 2014). Using less critical rhetoric than appearing in Hubbard (2016) and Woodside (2016a, 2016b), these three additional studies have direct comparisons of findings from symmetric and asymmetric testing. Additional studies (Fiss, 2007, 2011; Hsiao, Jaw, Huan, & Woodside, 2015; Woodside, 2013; Wu, Yeh, Huan, & Woodside, 2014) explicitly call attention to the benefits from embracing the case-based modeling paradigm and the greater usefulness of asymmetric (precise outcome) tests.

WHY BAD SCIENCE PRACTICES PERVADE EMPIRICAL MANAGEMENT AND SOCIAL SCIENCE

Hubbard (2016) describes the forces of inertia and barriers to shifting to the superior research paradigm of "statistical sameness testing" (what this present chapter refers to as "SPOT") – the resulting predictions in case-based modeling are somewhat precise because an accuracy hit ratio of 100% is rarely obtainable.

> What is the likelihood of the statistical sameness paradigm supplanting, or at least, paralleling, that of significant difference? This is a tall challenge, one made worse by two formidable and interrelated barriers. The first is that members of the significant difference paradigm

> cherish their conception of science and tend to look at alternative approaches to knowledge procurement with an air of suspicion, or even dismissiveness …. [They] wish to keep doing things the same way they have been done for decades. As a consequence, the sheer weight of academic inertia, fortified by researcher unawareness of how science makes headway, acts as a powerful antidote against the need for change of any kind. The second barrier is that all too often academicians are preoccupied with enriching their careers as scholars and are unconcerned with real-world knowledge development. (Hubbard, 2016, p. 228)

Related to the second barrier are pedagogical assessments that indicate acceptance only of the currently dominant paradigm. The following statements actually expressed by full professors reflect such reasoning. "SEM is standard practice. Everybody uses SEM, so I must do so." "I can't change [instruction content in the marketing research course] just because it's wrong." The second quote was supported by the following statement, "I don't have the time in the course schedule to teach SPOT." Fear of rejection is viewable as a separate causal condition. Protests against SPOT from the significant difference school do not center on NHST is wrong but on concerns that graduate students would not be able to publish their work unless the work used statistical significance testing (Hubbard, 2016; Schmidt, 1996).

For early career scholars, the low right condition in the Venn diagram in Fig. 1, may be in for a surprise. However, extensive evidence on peer review shows that papers with findings that contradict important viewpoints are nearly always rejected by reviewers (Armstrong, 1997). For example, a survey by Armstrong and Hubbard (1991) found that "'Editors of 16 psychology journals reported that reviewers dealt harshly with papers that contained controversial findings.' [Armstrong] … found that none of what he considers his twenty most important papers received full acceptance by reviewers" (Armstrong & Green, 2007). Adopting a stance somewhat hiding your true purpose via, "I come here to bury Caesar, not to praise him" – followed by accurate evidence contrary to this verbal statement is more likely to be successful than trying a full-frontal attack on a dominant paradigm. Reading Ordanini et al. (2014) might spring-to-mind as a successful execution this strategy. Gigerenzer and Brighton (2009) illustrate a full-frontal attack on regression analysis with a rich and deep set of evidence of good science practices; see also Armstrong (2012).

The start-ups of multiple catalytic actions on several fronts are often necessary to gain widespread adoption of a superior new technology (Woodside, 1996). Part of the solution for breaking through the barriers preventing good science practices surely is the approach taken by Montgomery (1975), McClelland (1998), Ordanini et al. (2014), and Ferguson et al. (2017) of including theory, data analysis, and findings using both NHST and SPOT. The outright banning of NHST reporting (Trafimow & Marks, 2015) represents a draconian solution. Describing and illustrating the findings and benefits of the new paradigm appearing in articles in elite journals (Frösén et al., 2016; Prado & Woodside, 2015) represent a third catalyst. Joining and becoming active in the world's leading organization on case-based modeling and estimating the accuracies of precise outcome predictions – COMPASSS.ORG – is a fourth catalyst. Participating in workshops to learn how to construct and test theory using algorithms (fuzzy-set qualitative comparative analysis) sponsored, for example, by COMPASSS.ORG, Global Innovation and Knowledge Academy (GIKA), and the Global Alliance of Marketing and Management Associations (GAMMA), is a fifth catalyst.

VISUALIZING BAD VERSUS GOOD SCIENCE PRACTICES

This section presents and describes visual outputs of bad and good science practices. Gigerenzer's (1991, p. 19) wisdom has great importance here, "Scientists' tools are not neutral." The current dominant logic in EMBS is bad science practice, that is, constructing theories from a foundation of regression analysis (MRA/SEM) – symmetric tests of relationships between variables showing differences are not equal to zero. The new logic in EMBS is good science, that is, constructing theories from a foundation of algorithms – asymmetric tests of complex antecedent screens indicating consistent occurrence of a specific outcome. The following examples of bad versus good practices make use of the data from the same study.

Fig. 2 presents a variable-based theory of antecedents and consequences for problem gambling (PG) from a study by Prentice and Woodside (2013). Fig. 2(a) presents the theory. Fig. 2(b) presents the findings. Fig. 2(a) Panel (a) includes the hypothesized directional relationships of and Fig. 2(b) panel (b) includes the empirical directional relationships of SES variables' impacts on problem gambling. Symmetric testing using MRA is the basis for both the theory construction and the data analysis. The core hypotheses are directional predictions (e.g., as age increases, PG increases). Panel (a) shows individual positive and negative associations for nine antecedents and PG: five casino customer socioeconomic status (SES) characteristics and four customer behaviors. The hypotheses are only directional and, as such, illustrate shallow theory and testing. As McCloskey (2002) and Hubbard (2016) emphasize, without a focus on quantities (i.e. precise outcomes) such theorizing is "worthless as science" (McCloskey, 2002, p. 55). Using directional hypotheses illustrates shallow research practice and disinformation. Such research lacks the "requisite variety" to describe, explain, and predict anomalies in relationships – and anomalies almost always occur in relationships.

For example, while age may have a positive association with casino PG, a number of young people are likely to be casino problem gamblers. (Note the shift from "problem gambling" to "problem gambler.") Discretizing cases (individual respondents' data) by age and severity of PG using quintiles results in 25 cells and with reasonably large sample sizes ($n \geq 100$), all 25 cells include a few to many cases even when the symmetric test indicates a highly significant

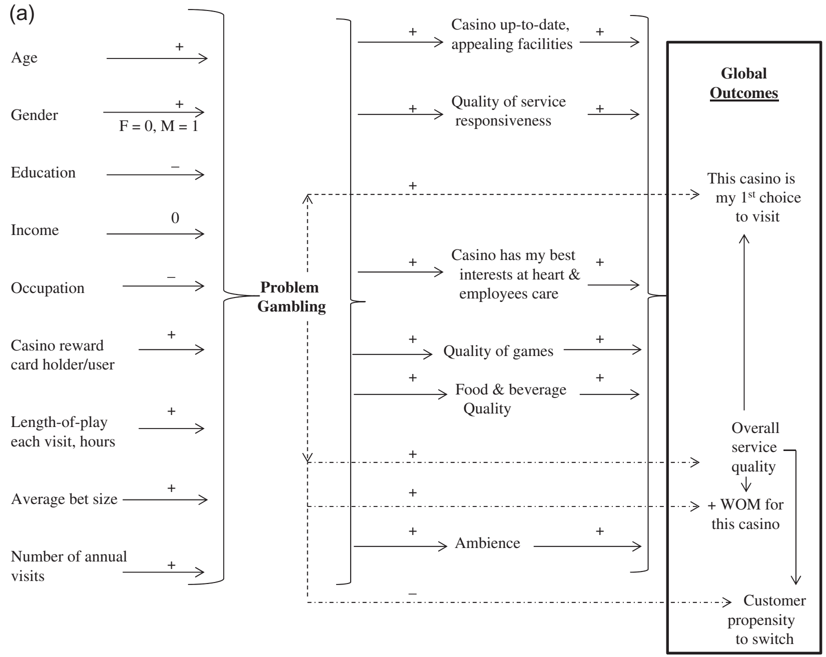

Fig. 2. Visual of Example of NHST Bad Science Practice: Theory and Findings of Antecedents and Outcomes of Problem Gambling. Panel (a) includes the hypothesized directional relationships of and panel (b) includes the empirical directional relationships of SES variables' impacts on problem gambling.

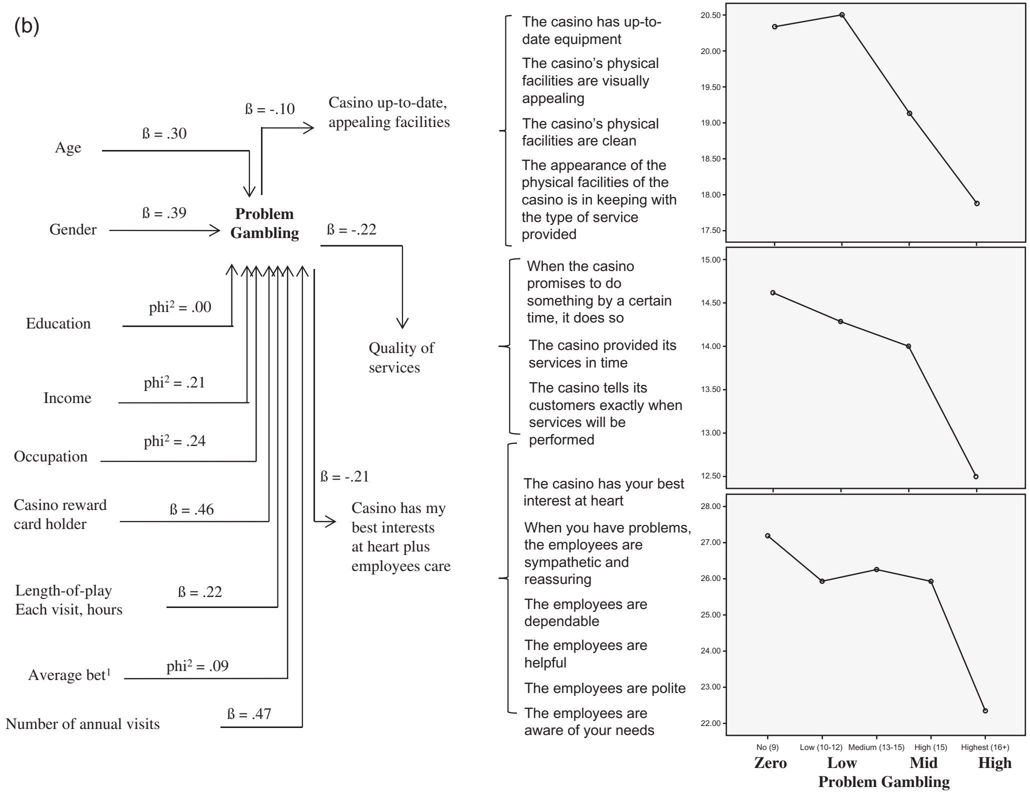

Fig. 2. (*Continued*)

positive relationship. Just reporting that the majority of cases are found in the main diagonal (young and not PG vs. old and PG) is shallow bad science. Young-and-PG cases and old-and-not-PG cases are not unexplainable blips but seeming anomalies worthy of theory construction and testing. "Four-corner theory construction" is the recognition that most XY associations for a simple X and a simple Y support the complexity theory tenet (Woodside, 2017) that all four associations occur: low X and high Y, high X and high Y, high X and low Y, and low X and low Y – even when the effect size of the directional hypothesis between X and Y is large.

An anomaly is a fact or case that does not fit received wisdom. "To a certain kind of mind, an anomaly is an annoying blemish on the perfect skin of explanation. But to others, an anomaly marks an opportunity to learn something perhaps very valuable. In science, anomalies are the frontier, where the action is" (Rumelt, 2011, pp. 247–248). Shifting from the current dominant variable-based logic to case-based logic increases the possibilities of describing, explaining, and predicting cases having anomalous properties. Shifting from variable-based to cases-based theory construction and data analysis are steps necessary to take to fully examine anomalies. Discretizing using quintiles (McClelland, 1998) or fuzzy-set scores (Ragin, 2008) is an adequate procedure for shifting successfully. Because cases tend to clump around the median and the cases in the bottom and top quintiles are actors of particular interest, dichotomizing cases into low and high scores is a bad practice in transitioning from variable-based to case-based modeling (cf. Fitzsimons, 2008). Iacobucci, Posavac, Kardes, Schneider, and Popovich (2015a, 2015b) offer an alternative and incorrect perspective that supports the bad science practice of dichotomizing data into cases with low versus high scores for a given variable. Except for naturally occurring dichotomous variables (e.g., gender), researchers should avoid dichotomizing continuous variables as Rucker, McShane, and Preacher (2015) recommend. However, Rucker et al. (2015) are mistaken and offer bad advice in recommending preserving the continuous nature of the variable and analyzing the data via linear regression and in recommending that regression remains the normative procedure in research involving continuous variables.

The findings in Fig. 2(b) include simple standardized regression weights testing the null hypotheses of zero associations. Note that the findings support the pattern of positive and negative hypotheses for the antecedent conditions to PG but not the positive hypotheses for the consequences of PG. Rather than positive relationships, the three consequences from PG to evaluating casino services are negative (as well as for the additional services shown in Panel (a) and included in Panel (b)). This pattern of findings leads Prentice and Woodside (2013) to entitle their article, "Problem gamblers' harsh gaze on casino services."

However, Prentice and Woodside (2013) overgeneralize and their theory and data analysis remain in the shallows. Not all problem gamblers gave a negative assessment of casino services as their study suggests. Shifting from a variable-based to a case-based theory and data analysis indicates 20% of customers high in PG provided positive assessments of casino services (Woodside, Prentice, & Larsen, 2015). By discretizing using quintiles and constructing and testing a four-corners' theory, the research leaves the shallows and adopts a requisite variety perspective – a deep dive in understanding, describing, and predicting problem gamblers as well as non-problem gamblers and the complex antecedent conditions indicating each of the four corners.

Fig. 3 shows the cases in the corners for PG and casino service assessments. While the distribution of shares of cases indicates a negative PG-assessment association in Fig. 3, cases appear in all 25 cells and this finding supports asking a series of "who" rather than "if" questions. Who are the problem gamblers giving positive versus negative casino assessments? Who are the non-problem gamblers giving positive versus negative casino assessments? The findings in Table 1 permit answering these questions. Table 1 provides asymmetric models – predicting precise outcomes in one direction such as customers providing highly positive assessments of casino services (Panel A in Table 1) and customers providing highly negative assessments of casino services (Panel B in Table 1).

The models in Table 1 are expressible by "computing with words" (Zadeh, 1996). For example, model 1 in Table 1, Panel A states that old female casino guests, low in education and income, high in occupational status, who are not problem gamblers, provide high positive assessments of casino services. However, the consistency index (0.76) for this prediction indicates a number of exceptions occur. The consistency index in asymmetric analysis is analogous to a correlation (r) and the coverage index is analogous to the "coefficient of determination" (r^2). Ragin (2008) provides details for computing consistency and coverage indexes. Woodside (2017) recommends models achieving very high consistencies (above 0.85) that are particularly useful for indicating sound theory and information for practice.

PRINCIPLES OF GOOD SCIENCE PRACTICE THAT ARE USUALLY MISSING IN MOST ARTICLES

Six good science practices that are usually missing in EMBS articles in elite and lower ranked journals appear inside the right-side circle in Fig. 1. Woodside (2016a, 2016b) provides additional discussion of these and additional good practices usually missing in research reports in EMBS journals.

SPOT is the first good science practice in the right-side of Fig. 1. This present chapter and Hubbard (2016) in particular explain why researchers should shift to using SPOT and leave the corrupt research practices of NHST behind. Reporting XY plots is very useful practice; Anscombe (1973) demonstrates that very different XY plots can occur for different data sets having the same mean, 30% of customers with zero to very low problem-gambling scores gave high scores on overall service quality

Contrarian type 2 cases: 39% of customers with zero to very low PG scores gave low scores on overall service quality

			Overall Service Quality Grps					
			1.00	2.00	3.00	4.00	5.00	Total
PG segments	None	Count	58	29	69	37	39	232
		% within PG segments	25.0	12.5	29.7	15.9	16.8	100.0
		% of Total	14.1	7.1	16.8	9.0	9.5	56.4
	1–2	Count	14	6	16	3	3	42
		% within PG segments	33.3	14.3	38.1	7.1	7.1	100.0
		% of Total	3.4	1.5	3.9	0.7	0.7	10.2
	3–4	Count	12	8	20	11	4	55
		% within PG segments	21.8	14.5	36.4	20.0	7.3	100.0
		% of Total	2.9	1.9	4.9	2.7	1.0	13.4
	5–6	Count	8	10	13	9	4	44
		% within PG segments	18.2	22.7	29.5	20.5	9.1	100.0
		% of Total	1.9	2.4	3.2	2.2	1.0	10.7
	7+	Count	15	6	14	1	2	38
		% within PG segments	39.5	15.8	36.8	2.6	5.3	100.0
		% of Total	3.6	1.5	3.4	0.2	0.5	9.2
Total		Count	107	59	132	61	52	411
		% within PG segments	26.0	14.4	32.1	14.8	12.7	100.0
		% of Total	26.0	14.4	32.1	14.8	12.7	100.0

48% of customers with high to very high problem-gambling scores gave low scores on overall service quality

Contrarian type 1 cases: 20% of customers with high to very high PG scores gave high scores on overall service quality

Fig. 3. Problem-Gambling Symmetric and Asymmetric Associations with Overall Service Quality. *Notes*: For the distribution of cases, the symmetric main effect is negative; phi $= .288$, $p < .081$. ANOVA findings indicate significant differences in overall service quality by PG segments that supports a significant symmetric negative main effect, means (standard errors) for the five PG segments from low to high: 9.82 (.10); 9.31 (.21); 9.67 (.19); 9.66 (.24); 9.05 (.26); $F = 2.68$, DF $= 4/406$, $p < .032$. The findings include contrarian type 1 cases: cases with high scores on the outcome condition that counters the negative symmetric main effect; the findings include contrarian type 2 cases: cases with low scores on the outcome condition that counters the negative symmetric main effect.

Table 1. Problem Gambling and Socio-Demographic Status Antecedent Conditions Indicating High or Negative Overall Casino Service Assessments.

Model	PGSI	Age	Gender	Education	Income	Occ Status	Title Status	Coverage		
								Raw	Unique	Consistency
Panel A: Four complex antecedent conditions indicate highly positive overall casino assessments										
1	○	●	○	○	○	○		0.16	0.10	0.76
2	●	○	●	○	○	●	○	0.14	0.06	0.81
3	○	○	○	●	●	●	●	0.05	0.94	0.92
4	●	○	●	●	●	●	●	0.08	0.02	0.84
Solution coverage = 0.30; solution consistency = 0.82										
Panel B: Eight complex antecedent conditions indicate highly negative overall casino assessments										
1			●	○	○	●	○	0.27	0.05	0.87
2	○	○	●	○	●	○		0.13	0.03	0.84
3	○	●	○		○	●	●	0.09	0.02	0.79
4	●	○	●	●		●	●	0.15	0.03	0.86
5	●	●	●	○		●		0.15	0.05	0.82
6	○	○	○	●	●	●	●	0.04	0.01	0.85
7	○	●		○	○	●	●	0.17	0.00	0.84
8	○	●	●	○	○	●		0.13	0.00	0.79
Solution coverage = 0.50; solution consistency = 0.83.										

Notes: PGSI = problem gambling severity index; "●"=high score; "o"=indicates low score; blank = absent, not relevant to the model.

standard deviation, and correlation. Even though Anscombe has one thousand plus citations via Google.com/scholar, the practice of including *XY* plots occurs rarely.

Second, studies in articles in leading journals frequently report statistically significant fit validities and no analysis for predictive validation of models using separate samples. Armstrong (2012) demonstrates accomplishing significant fit validity using a table of random numbers. Reporting only fit validity is bad science practice as Armstrong (2012), Gigerenzer and Brighton (2009), McClelland (1998), Morgenroth (1964), and Roberts and Pashler (2000) all stress. Fit validity indicates symmetric tests outperform asymmetric tests in accuracy; predictive validation supports the opposite conclusion (Gigerenzer & Brighton, 2009). The "critical issue is whether or not a model is useful in practice that is, does the model have high predictive validity when testing on additional samples not used in constructing the theories" (McClelland, 1998, p. 335). This perspective is known widely but rarely practiced in research reports in scholarly journals.

Third, theory construction for explaining, describing, and predicting anomalies rarely appears in elite and lower ranked journals. Given that anomalies are recognizable in nearly all data files, this observation may be surprising. However, the pervasive practice of bad science focusing on NHST via symmetric tests prevents scholars from diving deep into identifying and modeling anomalous cases to statistically significant directional relationships. Embracing complexity theory (Woodside, 2017) and case-based theory construction and testing will cause a substantial increase in the study of anomalies.

The fourth good practice is to use algorithms to test for complex outcome configurations. Similar to Armstrong's (2012) discussion on the bad practice of using stepwise regression analysis (like playing tennis without a net; something is bound to be significant if you include 8−25 terms in regression model), algorithm software permits the researcher to test for whatever complex configurations will indicate a precise outcome consistently. Researchers should include ex ante model construction of algorithms rather than just seeing what models that the software produces. Ferguson et al. (2017) elaborate on this tenet of good science practice.

Embracing tenets of complexity theory (Woodside, 2014, 2017) − the fifth good practice − nurtures the achievement of requisite variety, shifting to asymmetric from symmetric tests, moving away from NHST to SPOT, and leaving the shallows in EMBS. Complexity theory includes the following tenets. T.1: A simple antecedent condition may be necessary but a simple antecedent condition is rarely sufficient for predicting a high or low score in an outcome condition. T.2: A complex antecedent condition of two or more simple conditions is sufficient for a consistently high score in an outcome condition − the recipe principle. T.3: A model that is sufficient is not necessary for an outcome having a high score to occur − the equifinality principle. T.4: Recipes indicating a second outcome (e.g., rejection) are unique and not the mirror opposites of recipes of a different outcome (e.g., acceptance) – the causal asymmetry principle. T.5: An individual feature (attribute or action) in a recipe can contribute both positively and negatively to a specific outcome depending on the presence or absence of the other ingredients in the recipes. T.6: For high *Y* scores, a given useful recipe (i.e., model) is relevant for most but not all cases; coverage is less than 1.00 for any one recipe (e.g., a specific useful model may be accurate in predicting high outcome scores for the majority of cases (e.g., 7 of 8, 14 of 15, 25 of 27), but a few false positives occur) – thus, the expression, "SPOT." T.7: Exceptions occur for high *X* scores for a given recipe that works well for predicting high *Y* scores. T.8: Discretizing continuous variables using quintiles and cross-tabulating frequently identify 10–20% of the cases to be contrary to a medium-to-large symmetric main effect; consequently, modeling the four corners of configural two cross-tabbed conditions will deepen description, explanation, and predictive knowledge in research.

CONCLUDING REMARKS: READINGS AND CONSTRUCTING THEORY AWAY FROM THE SHALLOWS

In a study of the impact of articles appearing during 2004–2008 in the *Journal of Consumer Research*, Pham (2013, p. 412) reports, "Very few articles – less than 10% – get very well cited, and the vast majority – roughly 70% – hardly ever get cited. In other words, the vast majority of the research that gets published, even in our top journals – perhaps 70% of it – hardly has any measurable scholarly impact in terms of citations." Most of the journal articles in elite and lower ranked journals represent bad science via corrupt research practice. This conclusion follows from reading Gigerenzer and Brighton (2009), Hubbard (2016), Ragin (2008), and Woodside (2016c, 2017).

Read Hubbard (2016) to learn how bad science practice dominates today via symmetric NHST. Read Ragin (2008) to learn how to "redesign social inquiry" based on case-based theory construction and testing. Read Woodside (2017) for additional explanation of why embracing complexity theory is necessary for achieving requisite variety in theory construction and data analysis. During the current transition years from bad-to-good science practices, along with continuing to use bad science practices to break through the resistance barriers and forces of inertia supporting the dominant symmetric logic, report good science research practices as well in your research (e.g., Ferguson et al., 2017; Frösén et al., 2016; Montgomery, 1975; Ordanini et al., 2014).

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