Embrace Complexity Theory,

Perform Contrarian Case Analysis,

and Model Multiple Realities

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Abstract

This essay describes tenets of complexity theory including the precept that within the same set of data X relates to Y positively, negatively, and not at all. A consequence to this first precept is that reporting how X relates positively to Y with and without additional terms in multiple regression models ignores important information available in a data set. Performing contrarian case analysis indicates that cases having low X with high Y and high X with low Y occur even when the relationship between X and Y is positive and the effect size of the relationship is large. Findings from contrarian case analysis support the necessity of modeling multiple realities using complex antecedent configurations. Complex antecedent configurations (i.e., 2 to 7 features per recipe) can show that high X is an indicator of high Y when high X combines with certain additional antecedent conditions (e.g., high A, high B, and low C)—*and* low X is an indicator of *high Y as well* when low X combines in other recipes (e.g., high A, low R, and high S), where A, B, C, R, and S are additional antecedent conditions. Thus, modeling multiple realities—configural analysis—is necessary, to learn the configurations of multiple indicators for high Y outcomes and the negation of high Y. For a number of X antecedent conditions, a high X may be necessary for high Y to occur but high X alone is almost never sufficient for a high Y outcome.

Keywords: antecedent; configuration; contrarian case; fsQCA; model; necessary; outcome; sufficiency

For every complex problem, there is a solution

that is simple, neat, and wrong. (H.L. Mencken)

1. Introduction: beyond rote applications of regression analysis

The end is near. Time now for a new beginning! This essay elaborates on the perspective that the current symmetric-based dominant logic in research in the management sub-disciplines is less informative and less theoretically useful than the alternative logic of asymmetric testing (McClelland, 1998; Woodside, 2013a, 2013b). The contribution here provides details of why and how to use this relatively new theoretical stance and analytics in the management sub-disciplines.

The dominant logic in research in papers submitted to leading journals in the fields of marketing, management, finance, and international business includes question-and-answer surveys using 5 and 7 point scales and analyses of the resulting data using structural equation modeling; for example, about 7 of 10 submissions to the *Journal of Business Research* employ these features. The use of structural equation modeling (SEM) became popular in the 1980s and has grown to become central in the dominant logic in crafting and testing models well into the 21st century. SEM combines and extends factor analysis and multiple regression analysis (MRA). SEM and MRA are symmetric tests that report on the "net effects" of variables on a dependent variable with a set of independent variables.

Along with using SEM/MRA and structured scale measures, the current dominant logic includes the following features: collecting survey data via scaled responses from one person per organization with the respondent answering the questions one-time only; useable response rates less than 20 percent of the surveys sent to potential respondents; presentation of the fit validities of one-to-five sets of empirical models with no testing for predictive validity with holdout samples (see Gigerenzer and Brighton (2009) for a review of problems associating with not testing for predictive validity with holdout samples and how to do so); reporting of empirical models that include both significant and non-significant terms; no testing or reporting of contrarian cases in these papers—no recognition that the direction of impacts is the opposite of that found in the models reported for some of the respondents; and thus, no recognition of why the resulting models (empirical findings) explain little of the variance in the dependent variable (adjusted R^2's most frequently less than 0.20).

Even though SEM reports are usually elegant to contemplate, the limitations of employing the current dominant logic in the management sub-disciplines are tellingly severe. The limitations include requiring respondents transform their beliefs and evaluations to 5 or 7 point scales, the operational step of collecting answers from one person per organization or household rather than seeking confirmatory/negative answers from two or more respondents in the same organization (for an exception, see Cheng, Chan, and Li, 2013), modeling using net effects symmetric tools such as MRA or SEM when patterns of relationships in the data are asymmetric, and testing only for fit validity and not testing for predictive validity. However, describing such limitations is insufficient to achieve useful innovations to theory construction and testing. Proposing and showing useful research analytic innovations are necessary steps for achieving change—especially in moving early-career academic researchers away from using MRA and SEM only and to embrace the use of asymmetric theory construction and testing.

Question surveying from a distance severely limits the collection of contextual information; context is one of the two blades in Herbert Simon's metaphor of human decision making. "Human rational behaviour is shaped by a scissors whose blades are the structure of task environments and the computational capabilities of the actor (Simon, 1990, p. 1). Simon's scissors metaphor supports calls for "direct research" (Mintzberg, 1979)—to include the study of context as well as to craft isomorphic models of real-life thinking processes in these contexts (Woodside, 2011, 2013b). Asking questions alone to describe and explain decision processes requires a respondent to interpret the question, retrieve relevant information usually from long-term memory, edit the retrieved information for relevancy and self-protection, and report in a format and style usually to appear sane and accurate to some degree; responses following these steps quite often have little relationship to reality (Bargh & Chartrand, 1999; Nesbitt & Wilson, 1977). Verbal responses in answering questions require subjective personal introspections (SPI); SPI's frequently include accurate information only to a modest degree (Woodside, 2006) and frequently both attitudes and beliefs expressed following SPIs serve as poor predictors of future behavior.

The theoretical and practical value of asking respondents to convert their SPI thinking into 5 or 7 point scales joins with the lack of contextual data collection to result data of highly questionable value. As Mintzberg (1979) ruminants aloud to himself and to us:

> "Hmmmm …what have we here? The amount of control is 4.2, the complexity of environment, 3.6." What does it mean to measure the "amount of control"' in an organization, or the ‘‘complexity'' of its environment? Some of these concepts may be useful in describing organizations in theory, but that does not mean we can plug them into our research holus-bolus as measures. As soon as the researcher insists on forcing the organization into abstract categories—into his terms instead of its own—he is reduced to using perceptual measures, which often

> distort the reality. The researcher intent on generating a direct measure of amount of control or of complexity of environment can only ask people what they believe, on 7-point scales or the like. He gets answers, all right, ready for the computer; what he does not get is any idea of what he has measured. (What does “amount of control” [or “trust”] mean anyway?) The result is sterile description, of organizations as categories of abstract variables instead of flesh-and-blood processes. And theory building becomes impossible. (Mintzberg, 1979, p. 586)

Woodside (2013a) compares and contrasts the use of symmetric (e.g., MRA and SEM) versus asymmetric (e.g., analysis by quintiles and by fuzzy set qualitative comparative analysis) whereby symmetric tests consider the accuracy in high values of X (an antecedent condition) indicating high values of Y (an outcome condition) and low values of X indicting low values of Y where asymmetric tests consider the accuracy of high values of X indicating high values of Y without predicting how low values of X relates to values of Y. Might not seem that different but symmetric tests rarely match well with reality except for testing the association of two or more items to measure the same construct (coefficient alpha is a symmetric test and researchers seek high coefficient alphas (e.g., $r > 0.70$). Asymmetric tests reflect realities well given that the causes of high Y scores usually differ substantially from the causes of low Y scores (i.e., the principle of causal asymmetry, see Fiss, 2011); examples appear later in this essay of this principle.

Following this introduction, this treatise includes three complementary parts. First, tenets in complexity theory provides useful foundation for analyzing data—the nearly rote statements of main effects and rote applications of multiple regression analysis (MRA) appearing in most academic studies in management-related sub-disciplines ignore the complexities inherent in realities and apparent (with a little digging) in the data sets of academic studies. Second, contrarian case analyses confirm that substantial numbers of cases occur which display relationships that are counter to a negative (or positive) main effect between X and Y—even when the effect size is large of the reported X-Y relationship. For example, when X associates positively with Y with a correlation of 0.60 ($p < .001$), the same data set includes cases of high X and low Y and cases of low X and high Y; researchers ignore these contrarian cases in most reports even though examining such cases is highly informative. Third, using configural analysis of complex antecedent conditions, modeling of the multiple realities is possible and insightful—modeling the existence of a net effect of X for different numbers of additional independent variables offers a meager portion of the meal-of-information extractable by drilling deeper.

The study here is valuable in describing how complexity theory serves as a useful foundation for building and testing theory beyond the now dominant logic of applying MRA perspectives of net effects main and interaction terms. Embracing a complexity theory perspective (CTP) provides vision for explicit consideration of hypotheses counter to the dominant logic of presenting one theory per study. Thus, a CTP expands on Armstrong, Brodie, and Parsons' (2001) observation that advocating of a single dominant hypothesis lacks objectivity relative to the use of exploratory and competing hypotheses approaches—even though their "publication audit" of over 1,700 empirical papers in six leading marketing journals during 1984-1999 indicates that 3 of every 4 studies use only the single, dominant, hypothesis perspective.

The study here is valuable in describing how contrarian case analysis is useful in probing complexity theory tenets and building and testing new theory by developing compound outcome statements—descriptions and examples of such statements appear in section 3. The study here is valuable in bridging configural analysis using fuzzy set qualitative comparative analysis (fsQCA) with complexity theory in sub-disciplines of management (e.g., finance, marketing, organization science, and strategic management); such bridging expands on the contributions of Ragin (2008) in sociological methods, Fiss (2007, 2011; Meier & Donzé, 2012) in organization science, and Woodside and colleagues (2013a, b; Chung & Woodside, 2012; Schuhmacher, von Janda, & Woodside, 2013; Woodside & Zhang, 2013) in marketing.

Following this introduction, section 2 presents tenets in complexity theory. Section 3 describes how contrarian case analysis and findings show that cases occur contrarian to main effects having large effects sizes—most researchers usually ignore such contrarian cases both in formulating theory, examining data, and in predicting fit validity. Section 4 reports on models of the multiple realities that occur within each of several data sets. Section 5 concludes with the call to recognize the need to perform and report multiple models showing how high X associates with high Y in more than one model/path (being done to some extent now using MRA), how *low* X also associates with high Y in more than one model (rarely being done), and how models of the negation of Y are not the mirror opposites of models of high Y—"causal asymmetry" (Fiss, 2011; Fiss, Marx, & Cambré, 2013) occurs whereby complex antecedent conditions indicate the negation of Y are not simply the opposites of the recipe of simple conditions in the complex antecedent statements indicating high Y.

2. Complexity Theory Tenets

The literature on complexity theory is expansive and heads in several discernable directions. Anderson (1999) provides advances in theory and research on complexity theory relevant to organization science. Several useful studies expand on the insights of Anderson's (1999) and prior work (e.g., March and Simon, 1958) especially in the advancing complexity theory of organizational behavior through simulation methods (e.g., Davis, Eisenhardt, & Bingham, 2007; Huff & Huff, 2000). Urry (2005) provides a far-ranging literature review of complexity theory in the natural and social sciences and offers many useful insights. Example insights include the following perspectives, "Relationships between variables can be non-linear with abrupt switches occurring, so the same 'cause' can, in specific circumstances, produce different effects" (Urry, 2005, p. 4); "If a system passes a particular threshold with minor changes in the controlling variables, switches occur such that a liquid turns into a gas, a large number of apathetic people suddenly tip into a forceful movement for change (Gladwell, 2002). Such tipping points give rise to unexpected structures and events" (Urry, 2005, p. 5). Reporting on findings that include reversals in causal effects (e.g., positive to negative for the same antecedent with the same outcome) and reporting on tipping-point patterns in phenomena are primary foci in the present essay.

Simon's (1962) presentation of "the architecture of complexity" focuses on confirming and expanding on the tenet that complexity takes the form of hierarchy—the complex system being composed of subsystems that, in turn, have their own subsystems, and so on. Related to the central task of science relating to complexity and in general, in his essay, "Science seeks parsimony, not simplicity: searching for pattern in phenomena," Simon (1967) provides the following dictum, "The primordial acts of science are to observe phenomena, to seek patterns (redundancy) in them, and to redescribe them in terms of the discovered patterns, thereby removing redundancy. The simplicity that is sought and found beautiful is the simplicity of parsimony, which rests, in turn, on the exploitation of redundancy." Simon's working definition of parsimony is "pattern in the phenomena." The core focus of the present essay is to advocate formulating parsimonious theories—descriptions, explanations, and predictions of patterns in phenomena—and to show research method fundamentals for testing such theories. Implemented decision rules by firms are parsimonious patterns which are operational algorithms (e.g., Howard and Morgenroth, 1968; Morgenroth, 1964); related to consumer research profiles of buyers are examples of parsimonious patterns.

In marketing, famously, Kotler (1967, p. 1) pronounced, “Marketing decisions must he made in the context of insufficient information about processes that are dynamic, nonlinear, lagged, stochastic, interactive, and downright difficult.” Yet the substantial majority of studies in the nearly 50 decades since this pronouncement continue to ignore all the decision features that Kotler describes. Gummesson (2008) urges marketing scholars and educators to accept the complexity of marketing and develop a network-based stakeholder approach—balanced centricity—epitomized by the concept of many-to-many marketing. Gummesson (2008) calls for a rejuvenation of marketing.

> Reality is complex whether we like it or not. This is where network theory comes in. Its basics are simple; a network is made up of nodes (such as people or organizations) and relationships and interaction between those. Network theory is part of “complexity theory,” recognizing that numerous variables interact, that the number of unique situation is unlimited, that change is a natural state of affairs, and that processes are iterative rather than linear… But is balanced centricity a realistic objective or is it yet another professorial whim? I do not have the answer but I am convinced that if we keep fragmenting marketing and other business functions and duck complexity, context and dynamics, we will not move ahead. A change requires that we reconsider marketing basics and

> abandon mainstream methodological rigidity and move toward a more pragmatic and holistic research agenda. (Gummesson, 2008, p. 16, 17)

Scholars before Gummesson (2008) describe the need to reconsider mainstream methodological rigidity and move toward more pragmatic and holistic (i.e. patterns or systems) research agenda. Bass, Tigert, and Lonsdale (1968) offer evidence that the contention that the low R^2's obtained in regression analysis leads to false conclusions about the ability of socioeconomic variables as well as attitudinal measures to substantially explain variance in dependent variables since R^2 is a measure of a model's ability to predict individual rather than group behavior. McClelland (1998) goes further in stressing that most researchers do not really want to explain variance in dependent variables; what they want to do is to describe, explain, and accurately predict high scores in an outcome condition (i.e., create algorithms—decision rules—that work almost all the time in providing an effective decision and avoiding bad decisions). Without likely being aware of McClelland’s (1998) contributions to asymmetric thinking, research methods, and parsimony, Ragin (2000, 2006, 2008) relies on Boolean algebra rather than the dominating use of matrix algebra-based statistical methods to offer parallel insights and methods in sociological research and beyond.

Three additional points need stressing that relate to complexity theory’s focus on patterns in phenomena. First, “Scientists’ tools are not neutral” (Gigerenzer, 1991). Research methods and instruments shape the way we think and test theories. Thus, reviewers’ question whether a given paper is trying to make a contribution to theory or method sometimes misses the point that a research paper tries to do both—as is the case here. Second, reports of model confirmation relying only on fit validity need to stop; reports that partial regression coefficients in an MRA model are significant are insufficient findings and of limited usefulness. Analysts assume that models with a better fit provide more accurate forecasts. This view ignores the extensive research showing that fit bears little relationship to ex ante forecast accuracy, especially for time series. Typically, fit improves as complexity increases, while ex ante forecast accuracy decreases as complexity increases, a conclusion that Zellner (2001) traces back to Sir Harold Jeffreys in the 1930s (Armstrong, 2012). Gigerenzer and Brighton provides substantial empirical evidence supporting the focus for accuracy and theory advancement via predictive validity and not just fit validity.

Third, "Developing the full potential of complexity theory, especially in the social sciences, requires more rigorous theory development and fewer popular articles extolling the virtues of the 'new paradigm', more studies testing the new theories and fewer anecdotal claims of efficacy, greater development of tools tailored for particular contexts, and fewer claims of universality. Without such rigor, social scientists face the danger that, despite its high potential, 'complexity theory' will soon be discarded, perhaps prematurely, as yet another unfortunate case of physics envy" (Sterman and Wittenberg, 1999, p. 338). The following tenets (Ti) and sections of this essay are steps to contribute rigor in response to Sterman and Wittenberg's (1999) call to do so.

2.1 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.

$$X \nrightarrow Y \qquad (1)$$

For example, being male may be a necessity condition to play in the U.S. National Football League (NF) but being male is insufficient in describing or predicting membership in the NFL. Such modeling of complex antecedent conditions frequently ignores simple conditions and outcome associations that are nearly always true (e.g. males as a necessary condition for NFL membership).

A high score of a simple antecedent condition is insufficient in describing, explaining, or predicting a high score for most outcome conditions. The configurations in Figure 1 provide examples of this tenet. Figure 1 is a summary map of decision rules representing the decisions of a professional supermarket buying committee's process of accepting and rejecting new product offerings from manufacturers. The first question asked about a new product under consideration, "Does the manufacturer have a strong reputation?" If the answer is yes, this answer is not sufficient for the committee to accept the new product for the supermarket stores. The product under consideration has to pass a second hurdle, "Is the product significantly new?" If yes, the product is accepted by the selection committee. This one configuration describes one of several accept configurations in Figure 1.

Figure 1 here.

The first sufficiency model in Figure 1 describes a recipe consistency of two features—a strong manufacturer's reputation (R) and a new grocery product offered by this manufacturer that the committee judges to be significantly new (N). An offering having high membership in both conditions (R•N) indicates that the supermarket buying committee will accept (i.e., agree to buy) the new offering (i.e., R•N→Accept). The mid-level dot, "•", indicates the logical "and" condition in Boolean algebra, that is, R•N is equal to the lowest score for the recipe, R•N. Thus, if R = .05 and N = .99, then R•N = .05. Both R and N must be high for this recipe to indicate an "Accept" outcome. Figure 2 shows that high R•N is sufficient for "Accept" but not necessary—additional models (paths) appear in Figure 1 for reaching the "Accept" decision.

Figure 2 here.

A key point here is that the objective of building and examining configurations is not to explain variance but to describe and explain combinations of features which accurately indicate a high score in an outcome condition. The outcome condition could be a "Yes" decision by a supermarket buying committee to take-on a manufacturer's new product offering or the negation of doing so, "No", or other outcomes in different problems (e.g., a hiring decision; an employee promotion decision; a decision as to which university to apply to enter; to accept or reject a proposal to go to a movie or a marriage proposal; to select a vehicle to test drive and/or to buy). A sideways tilde ("~") indicates the negation score of a simple condition; thus, "~R" represents the negation of the reputation score in the supermarket buying committee example.

2.2 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.

Both nodes must have high scores in the first configuration in Figure 1 for an accept outcome (A) to occur: reputation (R) must be high and significantly new (N) must be high. If both R and N are high, then A=1.0 is the outcome predicted to occur. Model 2 represents this one configuration of a complete decision rule for the supermarket buying committee.

$$R \bullet N \rightarrow A \qquad (2)$$

A configuration score of 1.00 is the highest score possible for all configurations using Boolean algebra and calibrated scores. Calibrating scores is converting original values to a scale of 0.00 to 1.00. Ragin (2008) provides details on how and why scores are calibrated in creating and testing asymmetric theory using Boolean algebra versus doing so via matrix algebra and symmetrical tests (i.e., statistical hypothesis testing). Additional details on calibration appear below in this essay.

Note that calibrated scores can be dummy codes of 0.00 and 1.00 or calibrated scores can range between 0.00 and 1.00. From the information in Figure 1, consider a manufacturer's reputation includes three levels: weak/low, average, and strong/high. These three levels can be calibrated to equal 0.00, 0.50, and 1.00. The benefits of calibrating scores and using Boolean algebra include the ability to plot complicated statement on the X axis to test the consistency of asymmetric relationships between X and Y. For example, is the statement accurate that all decisions where R•N = 1.00 indicate that Y = 1.00? Consider the simulated findings from a thought experiment of thirty supermarket buying decisions testing the R•N complex antecedent conditions in the XY plot in Figure 2—a buying committee made decisions one day on 30 new products being offered by 30 different manufacturers.

Note that the X-axis in Figure 2 displays R•N and not R or N. R•N is a combinatory statement. For this introduction, R•N can take on two membership scores (0.0, 1.0). Note that when R•N=1.0, nearly all cases are accepted consistently—11 of 12 cases or .0.97 of the R•N cases are accepted. The coverage by all the accepted cases by this model is high as well; this model (R•N) represents 11 of the 16 accept cases (coverage = 11/16 = 0.69). The two indexes, consistency and coverage, indicate the usefulness of a model in explaining high outcome scores. Consistency is an asymmetric metric analogous to the symmetric correlation metric; coverage is an asymmetric metric analogous to the symmetric "coefficient of determination" (i.e., r^2). Table 1 shows the calculations for consistency and coverage for the R•N model in the thought experiment.

Table 1 here.

A useful rule of thumb to apply: for a model to be predictive of high scores for an outcome condition, consistency should greater than 0.80 and coverage should be greater than .01 (cf. Ragin, 2008). A model with high consistency and very low coverage score indicates a rare bird—a model for a rare case among the cases of data—whereby this rare case associates with a high outcome score. Doug Flutie (retired American NFL and Canadian league football player) is one such rare bird: a quarterback "too short to play quarterback and win" who consistently won games. Flutie would have a high score for short (S) and in the NFL draft for quarterbacks, not short (~S = 1.00) is a requirement in all NFL teams' selection models. Thus, Flutie was almost not selected by any NFL team in the draft year he was available even though he was a Heisman Trophy winner the year of his draft (i.e., Flutie was selected as the best college football player nationally). Flutie is short; his height is less than 5′10″ (1.778 meters) when almost all NFL quarterbacks are tall (≥ 6.0′).

2.3 T.3: A model that is sufficient is not necessary for an outcome having a high score to occur—the equifinality principle.

Additional paths occur for reaching an accept decision in Figure 1. Table 2 summarizes six paths appearing in Figure 1 leading to an accept decision and six paths leading to a reject decision. Equifinality is the principle that multiple paths occur which lead to the same outcome. The occurrences of different paths usually do not occur with the same frequency among the set of paths. Complexity theory informs that the equifinality principle that the occurrences of anyone feature may not be necessary for reaching a given outcome. For example, a high manufacturer's reputation is not necessary as an antecedent for all accept decisions to occur.

Table 2 here.

2.4 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.

The causal asymmetry principle indicates that the study of the causes of acceptance often tells us very little about the causes of failure. Consequently, separate asymmetric models of failure (or other outcomes besides the original focus of a study on success or other positive condition) are necessary if a researcher seeks to describe and explain success versus failure, promotion versus dismissal, hiring versus rejection, and so on. The causal asymmetry principle serves as a foundation principle of complexity theory in research on "highly reliable organizations" (HROs) (Weick & Sutcliffe, 2001, 2007; Weick, Sutcliffe, & Obstfeld, 1999). Weick and Sutcliffe (2001) identify five characteristics of HROs as responsible for the "mindfulness" that keeps them working well when facing unexpected situations: preoccupation with failure; reluctance to simplify interpretations; sensitivity to operations; commitment to resilience, and deference to expertise.

The causal asymmetry principle and the recipe principle support the suggestions that the study of "key success factors" (KSFs) (Cooper, 1993; Di Benedetto, 1999) using a net effects approach (Cooper, 1993; Di Benedetto, 1999) to explain and describe success is misleading and insufficient. No one factor is sufficient or likely necessary for success and research focusing only on success is unlikely to be very informative about the causes of failure. The literature on KSFs suggests the certain activities consistently associate with success and never with failure (e.g., submitting products to customers for in-use testing, Di Benedetto, 1999), while the literature focusing on recipes proposes and finds that the same attribute can either foster or inhibit new service adoption, depending on how it is configured with other attributes (Ordanini, Parasuraman, & Rubera, 2014; Prado and Woodside, 2014). This finding and prior findings that an attribute can contribute positively and negatively to the same outcome depending upon the other ingredients specific recipes follows from the fifth principle of complexity theory.

2.5 T.5: An individual feature (attribute or action) in a recipe can contribute positively or negatively to a specific outcome depending on the presence or absence of the other ingredients in the recipes.

The findings in Figure 3 illustrate this fifth complexity principle. The findings are from a study of customer evaluations of services received from a beauty parlor and health spa (Wu et al., 2014). Four recipe models appear in Figure 3 for customer evaluations of quality of the work by the service professional experienced by the customer. Notice that the absence of a companion visiting the beauty parlor and health spa contributes positively in the first three models but negatively in the fourth model appearing at the top of Figure 3. The first three models include youthful customers and the fourth model includes older customers in the recipes. Rather than making blanket statements that older or younger customers rate the work of service professionals highly positively with or without being accompanied by a companion, each of the four recipes include a unique blend of ingredients to indicate that high scores on these recipes associated with high scores on the same outcome.

Figure 3 here.

2.6 T.6: For high Y scores, a given recipe is relevant for some but not all cases; coverage is less than 1.00 for any one recipe. T2.7: a few exceptions occur for high X scores for a given recipe that works well for predicting high Y scores.

Note in Figure 3 that for 9 of the 11 cases with high X scores also have high Y scores for model 1 in the XY plot. For the 2 cases having low Y scores with high recipe (X) scores, some additional ingredient would need to be identified to shift these two cases to the left without also shifting the other 9 cases high in X. Such theory to analysis to theory to analysis pondering is a central aspect for improving on the informativeness of recipes.

3. Contrarian Case Analysis

From a study of employees' evaluations of their work environments including their overall happiness with their jobs, Table 3 illustrates the occurrence of contrarian cases that run counter to a large main effect. This study merges two data files; the first file includes the employees' job evaluations and the second file includes their supervisors' evaluations of the work performances of these same employees.

Table 3 here.

Table 3 reports a quintile analysis of hospitality employee happiness and their managers' in-role performance (IRP) evaluations (Hsiao, et al. 2015). A quintile analysis includes dividing the respondent cases from the lowest to highest quintile for each measured construct and examining the relationships among two or more constructs (McClelland, 1998). Even though the findings for the total sample are not significant statistically, note the modest positive relationship—14 versus 4 employees very low in happiness are very low versus very high in employees' in-role performances (IRP), respectively. The distribution of the 49 very happy employees includes 14 with very high IRP scores and only 7 with very low IRP scores. The key point here relates to the occurrence of employees unhappy to very unhappy who have high to very high IRPs (10+4+11+13=38 cases or 38/247 or 15.4% of the total cases) as well as employees happy to very happy having low to very low IRPs (9+10+7+6=32 or 32/247 or 13.0% of the total cases. Thus, more than one-fourth of the total cases in the study exhibit two relationships counter to the symmetric relationship that happy employees are productive employees and unhappy employees are unproductive employees.

Hsiao et al. (2015) were able to offer asymmetric empirical models via qualitative comparative analysis for all four sets of relationships: unhappy and highly unproductive employees, unhappy and highly productive employees, happy and highly unproductive employees, and happy and highly productive employees. The state of happiness alone was not sufficient or necessary in their study for low or high IRP. However, employees' high IRP was sufficient for predicting high "Customer-Directed Extra Role Performances" (CDERP)—that is, "going beyond the call of duty" and doing extra actions to insure high customer happiness.

The Hsiao et al. (2015) findings on contrarian case responses are illustrative of usual occurrences among large data sets ($n \geq 100$). Even when an effect size is large between two variables, cases exist in almost all large data sets that run counter to the main effects relationship. Hypothesizing main effects and moderating effects only without examining and explaining such contrarian cases represents over simplistic theorizing and handing of a data set.

4. Modeling Multiple Realities

Examples of modeling multiple realities here appear in the Wu et al. (2014) study of customer evaluations of beauty parlor and health club visits. Table 4 provides examples of additional models of equifinal solutions whereby high scores on these models (i.e., complex X recipes) indicate high scores on the outcome conditions. Note in Table 4 that models include indicators of high scores for arouse pleasure, delivered service quality, effective treatment, and high value for the money. Each set of models includes different ingredients for gender; separate models include female and ~female (i.e., male). This finding illustrates the point that reporting a main effect for gender is an inadequate representation of the impact of gender on high scores for any of the four outcome conditions. Similar conclusions are supportable for the other ingredients in the four sets of models. However, high education is a necessary condition for the effective treatment outcome condition in Table 4—both of the two useful models for this outcome condition include education as an ingredient.

Table 4 here.

Figure 4 presents Venn diagrams as a way of illustrating the possibilities of the presence and absence of ingredients in complex antecedent conditions (i.e., recipes) indicating high scores in an outcome condition. For example, for demographics 16 configurations are possible visually in Figure 4.

Figure 4 here.

Actually 81 combinations are possible if you consider any one of the features having three possible impacts within a recipe: high score (e.g., old age or A), low score (e.g., young age or ~A) and age not an ingredient in the recipe). Both theory and the mechanics of the software program (available for free at fsQCA.com) are useful bases for interacting with data for information on relevant recipes. Such analyses provide a useful match among the tenets of complexity theory and the inherent complexity of relationships in data.

5. Conclusion

Prior studies (e.g., Armstrong, 2012; Bass, et al., 1968; McClelland, 1998; Montgomery, 1975) identify serious problems with the near total reliance by most researchers on symmetric statistical tests and difficulties in achieving theory advances relying on such tools (Gigerenzer, 1991). Gigerenzer (1991) and McClelland (1998) call attention and demonstrate the value of using asymmetric tests to both advance theory as well as provide useful empirical models of the occurrence of multiple realities. Ragin (2008) has been the principal advocate in the behavioral sciences along with Gigerenzer (1991) and Armstrong (2012) on advancing new competencies in the theory and research relevant for advancing theory-crafting and analytical skills of academic researchers in the sub-disciplines of management. Because the body of work and rigorous tools relating to complexity theory applications and fsQCA is growing in the management sub-disciplines, the present dominant logic of MRA/SEM and survey research features described in this essay will end during the second decade of the 21st century. At least this prediction is what this essay advocates and attempts to show how to accomplish.

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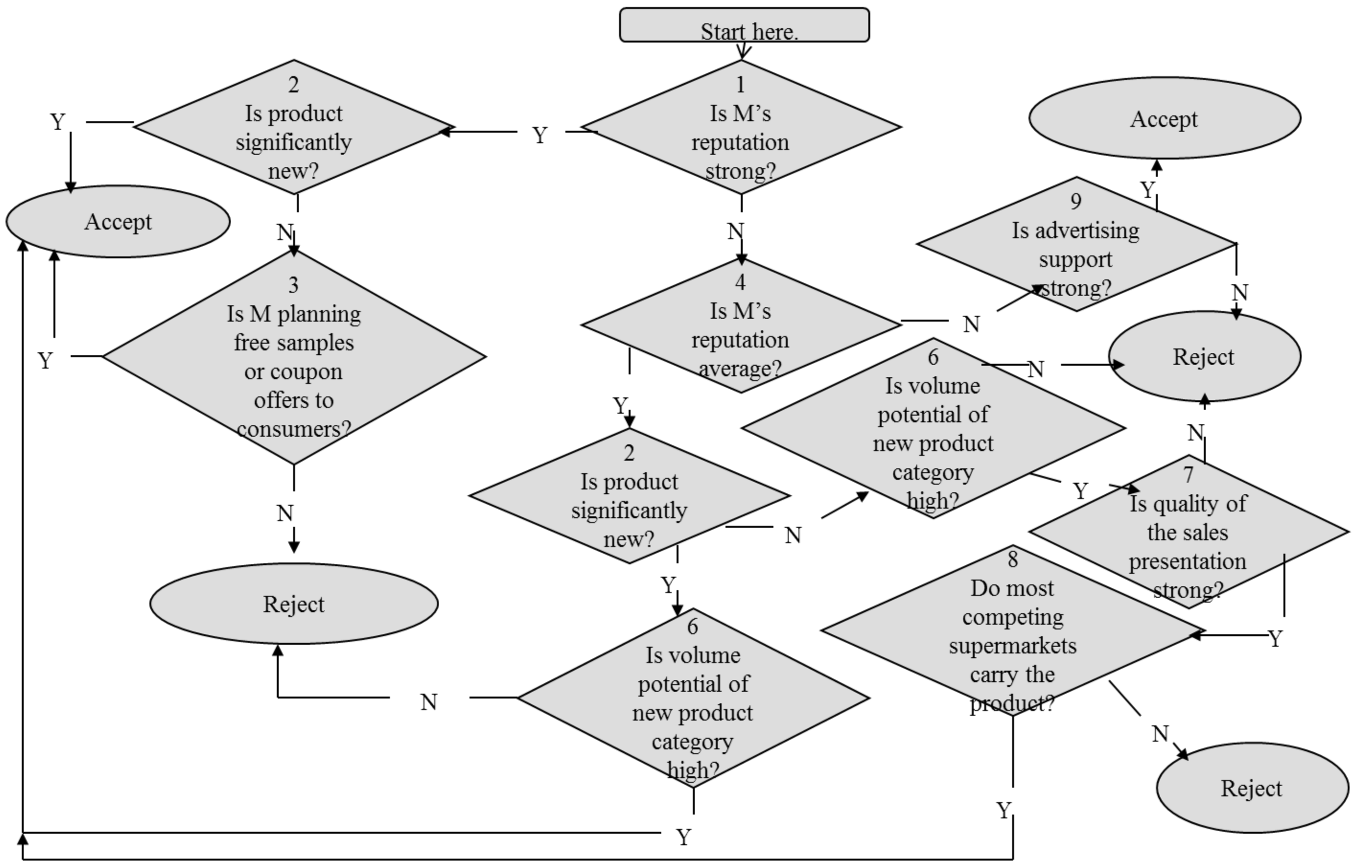
Figure 1
An Ethnographic Decision Process Model of Supermarket Committee Buying Decisions of a Manufacturer's (M's) New Product Offering



Source: adapted from Montgomery (1975).

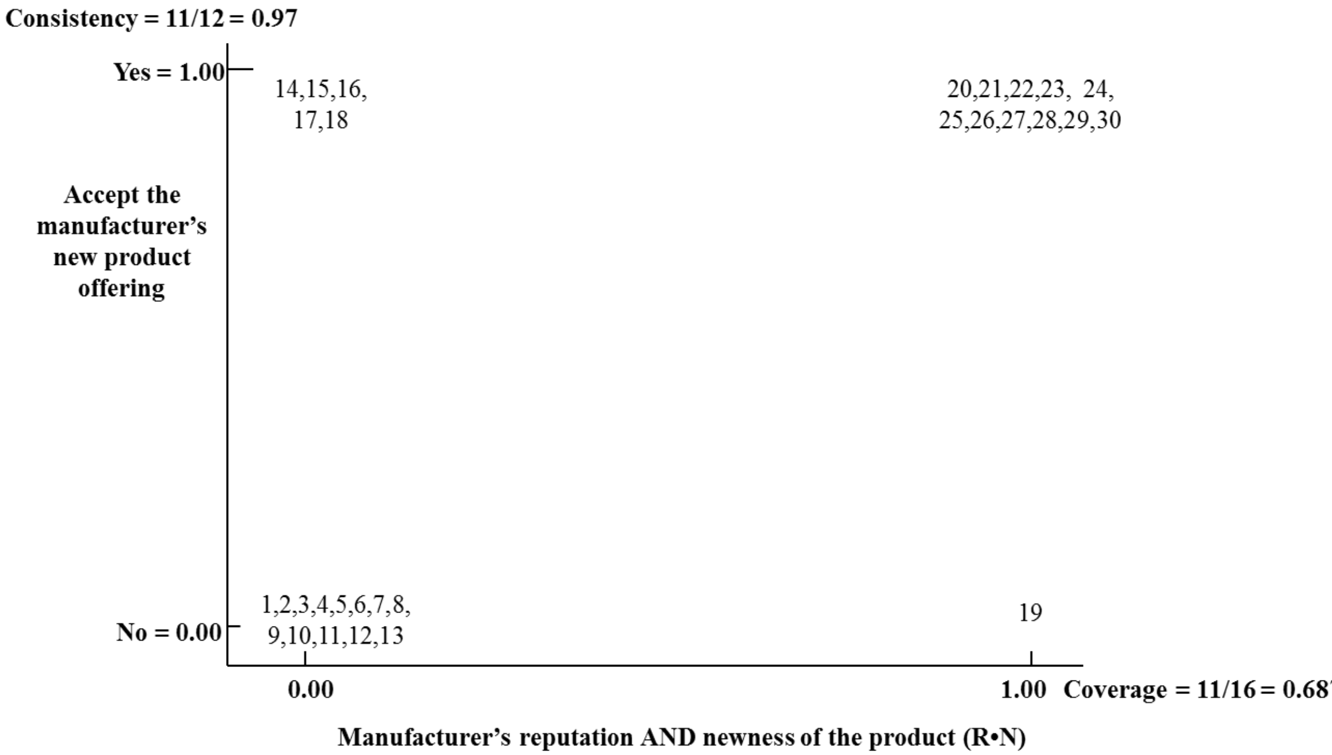


Figure 2
Thought Experiment for Thirty Decisions (n = 30) of a Complex Antecedent Condition and a Simple Outcome Condition: Supplier Reputation and Newness of Grocery Product Association with Decision to Carry the Product

Note. In this example, each number is a case identification and represents the plot of one decision. Note that the high R•N scores has high consistency with "Yes" (accept) but consistency is not 100 percent. Also note the relationship is asymmetric; low scores on R•N associate with both low and high scores on the outcome condition—more than one recipe is available to get to an accept condition. As in real-life, most outcomes are to reject the new product proposals.

Table 1
Calculating Consistency and Coverage for a Complex Antecedent Condition and an Outcome Condition

Case	R•N	A	Minimum (R•Ni, Ai))	Case	R•N	A	Minimum (R•Ni, Ai)
1	0.0	0.0	0.0	16	0.0	1.0	0.0
2	0.0	0.0	0.0	17	0.0	1.0	0.0
3	0.0	0.0	0.0	18	0.0	1.0	0.0
4	0.0	0.0	0.0	19	1.0	0.0	0.0
5	0.0	0.0	0.0	20	1.0	1.0	1.0
6	0.0	0.0	0.0	21	1.0	1.0	1.0
7	0.0	0.0	0.0	22	1.0	1.0	1.0
8	0.0	0.0	0.0	23	1.0	1.0	1.0
9	0.0	0.0	0.0	24	1.0	1.0	1.0
10	0.0	0.0	0.0	25	1.0	1.0	1.0
11	0.0	0.0	0.0	26	1.0	1.0	1.0
12	0.0	0.0	0.0	27	1.0	1.0	1.0
13	0.0	0.0	0.0	28	1.0	1.0	1.0
14	0.0	1.0	0.0	29	1.0	1.0	1.0
15	0.0	1.0	0.0	30	1.0	1.0	1.0
				Σ	12.0	16.0	11.0

Consistency (R•Ni ≤ Ai) = Σ (min (R•Ni, Ai) / Σ (R•Ni) = 11.0 / 12.0 = 0.96667

Coverage (R•Ni ≤ Ai) = Σ (min (R•Ni, Ai) / Σ (Ai) = 11.0 / 16.0 = 0.6875

Note. R = manufacturer's reputation; N = product newness; A = accept the product.

Table 2
Management Decision Paths Leading to Supermarket Buying Committee Adopting versus Rejecting Manufacturers' New Product Proposals

Path	Boolean Expression	Key
1. 1-2	R•N →A	R = Reputation; N = New; A = Accept
2. 1-2-3 (a)	R•~N•F→A	F= Free samples
3. 1-2-3 (b)	R•~N•~F→R	~ = Not; R = Reject
4. 1-4-9	~R•~RA•S→A	RA= Reputation average; S = ad support
5. 1-4-9 (b)	~R•~RA•~S→R	
6. 1-4-2-6 (a)	~R•RA•N•V→A	V = Volume potential
7. 1-4-9-6 (b)	~R•RA•N•~V→R	
8. 1-4-2-6 (b)	~R•RA•~N•~V→R	
9. 1-4-2-6-7	~R•RA•~N•V•~Q→R	
10. 1-4-2-6-7-8	~R•RA•~N•V•Q•C→A	Q = quality of sales presentation
11. 1-4-2-6-7-8 (a)	~R•RA•~N•V•Q•C→A	C = Competitors' carry new product
12. 1-4-2-6-7-8 (b)	~R•RA•~N•V•Q•~C→R	

Notes. Mid-level dot ("•") indicates the conjunctive "and". The horizontal arrow ("→") points to an accept or reject outcome.

Model[1]	raw coverage	unique coverage	consistency
1 ~compan*~servicew*housek*female*~educ_c*~age_c	0.025859	0.025859	0.941345
2 ~spa_expend_c*~compan*~servicew*~housek*~female*educ_c*~age_c	0.005423	0.005423	0.938776
3 spa_expend_c*~compan*servicew*~housek*~female*~educ_c*~age_c	0.004401	0.004401	0.957265
4 spa_expend_c*compan*servicew*~housek*female*educ_c*age_c	0.033443	0.033443	0.928026

solution coverage: 0.069127
solution consistency: 0.935638

Notes. [1] For example, model 1 states a case (customer) with a high score for no companion, not a service worker, a housekeeper, female, with low education and young will give a high score in service professional evaluations.
2 Note that the presence of companion contributes positively and negatively to the outcome (high score in people_q) depending on the additional antecedents in each of these four complex antecedent conditions—it is not so much a question of whether or not companion influences the outcome but under what circumstances (contingencies) companion does so.

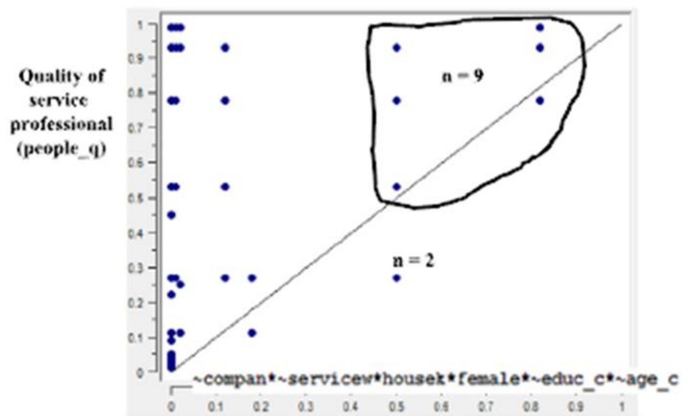


Figure 3 XY Plot of Model 1

Demographic, companion, and beauty salon/spa expenditure algorithm models predicting high people Q (service professional evaluations)
Source: Table 7 in Wu, et al. (2014, p. 1657).

Table 3
Hospitality Employees' Happiness and Managers' Evaluations of Employees' In-Role Performances

			In-Role Performance Quality (IRP)					
			Very low				Very high	
			1.00	2.00	3.00	4.00	5.00	Total
Very low	1.00	Count	14	8	13	10	4	49
		% within happy_segs	28.6%	16.3%	26.5%	20.4%	8.2%	100.0%
Happiness Quintiles for Hospitality Employees	2.00	Count	12	14	10	11	13	60
		% within happy_segs	20.0%	23.3%	16.7%	18.3%	21.7%	100.0%
	3.00	Count	10	9	9	4	7	39
		% within happy_segs	25.6%	23.1%	23.1%	10.3%	17.9%	100.0%
	4.00	Count	9	10	14	6	11	50
		% within happy_segs	18.0%	20.0%	28.0%	12.0%	22.0%	100.0%
Very high	5.00	Count	7	6	10	12	14	49
		% within happy_segs	14.3%	12.2%	20.4%	24.5%	28.6%	100.0%
		Count	52	47	56	43	49	247
		% within happy_segs	21.1%	19.0%	22.7%	17.4%	19.8%	100.0%

Possibly surprising findings: cases do occur of very unhappy employees with very high IRP scores and vice versa.

Notes. Total sample: $\varphi = .259$; $p < .413$; $\varphi^2 = .07$ (very small effect size). Q1 and Q5 happiness and five quintiles for IRP: $\varphi = .299$, $p < .068$; $\varphi^2 = .09$ (medium effect size). Comparing Q1and Q5 for both happiness and IRP: $\varphi = .478$, $\varphi^2 = .228$ (medium-to-large effect size).

Table 4
Four Sets of Models for Customer Evaluations of Experiencing Four Service Facets

A. Models for Arouse Pleasure

	raw coverage	unique coverage	consistency
educ_c*servicew*~housek*~female	0.016186	0.008217	0.968085
educ_c*age_c*servicew*~housek	0.106008	0.098040	0.904675
~educ_c*~age_c*~servicew*~housek*~female	0.021131	0.021131	0.894578
~educ_c*~age_c*~servicew*housek*female	0.032941	0.032941	0.897287

solution coverage: 0.168297
solution consistency: 0.903552

B. Models for Delivered Service Quality

	raw coverage	unique coverage	consistency
educ_c*servicew*~housek*~female	0.015396	0.007849	0.972341
educ_c*age_c*servicew*~housek	0.101705	0.094159	0.916515
~educ_c*~age_c*~servicew*housek*female	0.031936	0.031936	0.918605

solution coverage: 0.141491
solution consistency: 0.918635

C. Models for Effective Treatment

	raw coverage	unique coverage	consistency
educ_c*servicew*~housek*~female	0.019602	0.019602	0.972340
educ_c*~age_c*~servicew*housek*female	0.036459	0.036459	0.865580

solution coverage: 0.056061
solution consistency: 0.900138

D. Models for High Value for the Money

	raw coverage	unique coverage	consistency
educ_c*servicew*~housek*~female	0.017191	0.017191	0.919149
~age_c*~servicew*housek*female	0.052805	0.052805	0.862809
~educ_c*~age_c*~servicew*~housek*~female	0.025388	0.025388	0.960844

solution coverage: 0.095384
solution consistency: 0.897081

Source: Table 11a in Wu et al. 2014, p. 1664,

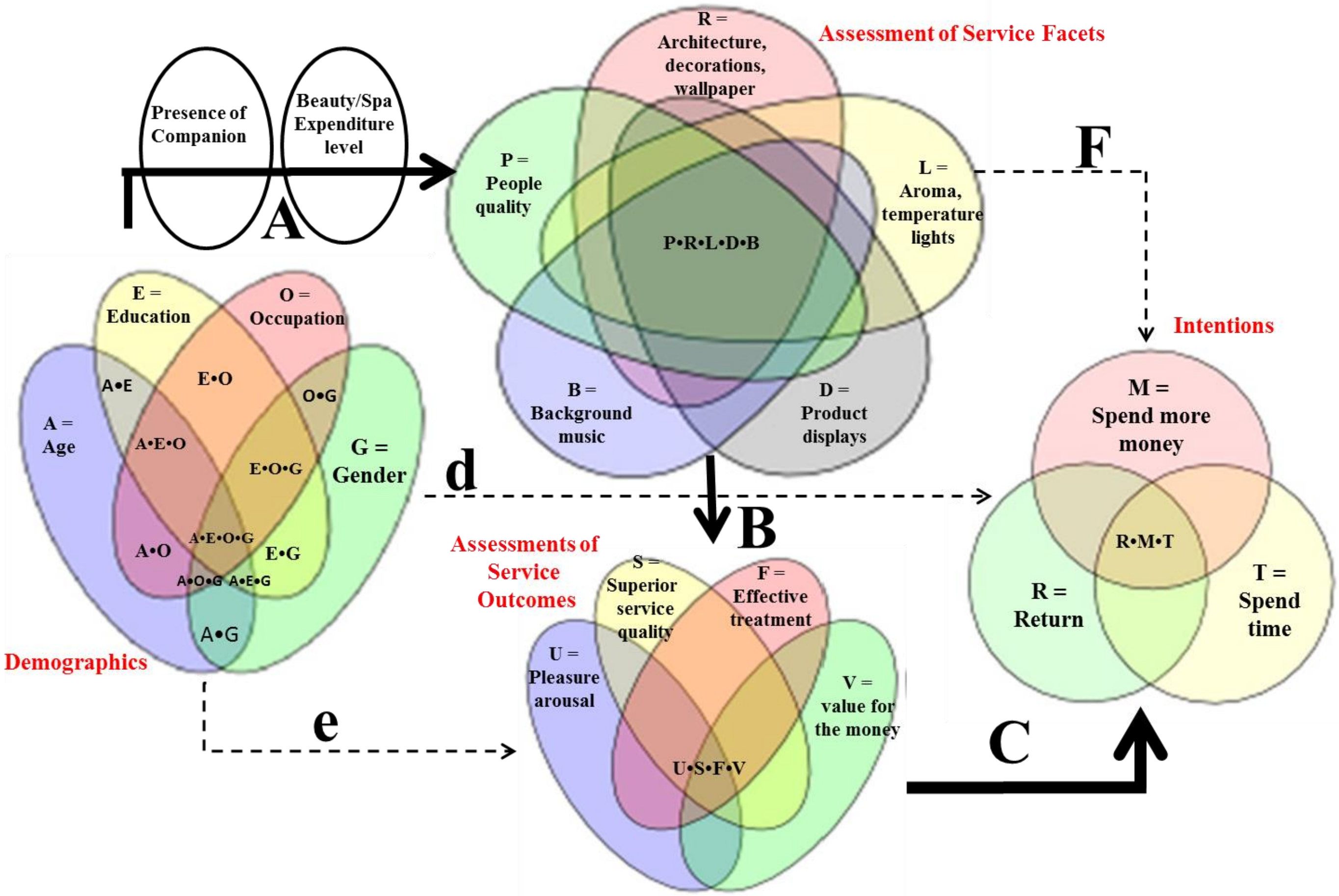


Figure 4
Modeling Multiple Realities