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Triple Sense-Making of Findings from Marketing Experiments Using the Dominant Variable Based-Logic, Case-Based Logic, and Isomorphic Modeling

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Abstract

The study describes the complementary benefits of model-building and data analysis using algorithm and statistical modeling methods in the context of unobtrusive marketing field experiments and in transforming findings into isomorphic management models. Relevant for marketing performance measurement, case-based configural analysis is a relatively new paradigm in crafting and testing theory. Statistical testing of hypotheses to learn net effects of individual terms in multiple regression analysis is the current dominant logic. Isomorphic modeling might best communicate what executives should decide using the findings from algorithm and statistical models. We test these propositions using data from an unobtrusive field experiment in a retailing context that includes two levels of expertise, four price-points, and presence versus absence of a friend ("pal" condition) during the customer-salesperson interactions (n=240 store customers). The analyses support the conclusion that all three approaches to modeling provide useful complementary information substantially above the use of one alone and that transforming findings from such models into isomorphic management models is possible.

Key words: configural analysis; field experiment; fuzzy set qualitative comparative analysis; multiple regression analysis; isomorphic management model

JEL classification: C18; C93; D12

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1. Introduction

This article presents nitty-gritty details and discusses the benefits resulting from comparing case-based algorithms and variable-based dominant-logic of statistical modeling and testing of hypotheses using the same set of data. The objective here is to demonstrate Gigerenzer's (1991) conclusion that "Scientists' tools are not neutral"—that is, the tools applied affect how theory is (re)constructed and the conclusions that follow from data analysis using these tools.

The study provides an example of building isomorphic-management models by transforming findings from tests of algorithm and statistical models into cognitions-in-context modeling for management decisions. Thus, the study shows how to use tools to construct effective contingency decisions that apply Simon's (1990) perspective—human rational behavior requires recognizing the influence of configurations of cognitions and contexts.

This study illustrates the high value in using both multiple regression analysis (MRA) and an algorithm approach, fuzzy set qualitative comparative analysis (fsQCA), for acquiring unique and complementary information from marketing data. This study is unique and valuable in actually showing how configural analysis complements statistical analysis of how marketing treatment variables (e.g., price and salesperson messages) and a measured consumer variable (a customer characteristic brought into the specific selling-buying context) affect purchase and profit.

The study is also unique in demonstrating how to convert algorithm and statistical modeling into isomorphic management models. The study examines statistical and configural modeling using data from an unobtrusive field experiment. The paper presents visuals of nuances in the analyses to deepen understanding of the benefits resulting from modeling and doing data analyses using all three approaches to testing and improving theory. While Wagemann and Schneider (2012) propose that steps in applying both statistical and algorithm analytical methods are useful, this study appears to be the first to actually show the value in doing so. The study goes beyond doing both by suggesting statistical, algorithm, isomorphic-management modeling (SAIM) as a step toward achieving use-by-executives of findings from testing statistical and algorithm models.

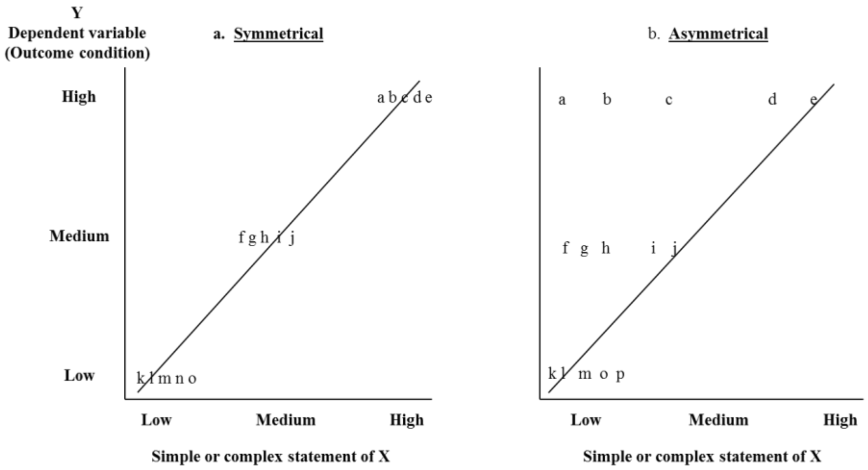
Case-based algorithms stress the reality of equifinality—multiple recipes that occur in their association with a high score in an outcome: the issue is never whether or not a variable has a significant net effect on a dependent variable. Variable-based studies focus on the finality of whether each variable is valuable or not, alone or in an interaction of variables, in predicting the value of a dependent variable: the primary issue is on reporting the "net effect"—that is, the direct plus indirect influence of each independent variable on a dependent variable.

Case-based algorithms stress the reality of causal asymmetry (Fiss, 2011; Ragin, 2008)—that is, the idea that the causes leading to the presence of an outcome of interest may be quite different from those leading to the absence of the outcome.

This view stands in contrast to the common correlational understanding of causality, in which causal symmetry is assumed because correlations are by their very nature symmetric; for example, if one models the inverse of high performance, then the results of a correlational analysis are unchanged except for the sign of the coefficients (Fiss, 2011).

Ragin (2008) expands on two considerations. First, the combination of three-to-six antecedent conditions presents a level of complexity not easily interpreted in statistical modeling of three-way to six-way interaction effects in MRA. Second, in real-life relationships of configurations and an outcome condition (e.g., purchase or high profit) are asymmetrical—more than one combination occurs for a configurative score representing an algorithm and an outcome condition. Statistical modeling applies and tests for the assumption of symmetry—high scores for the outcome condition associate with high scores for each independent variable and low scores for the outcome condition associate with low scores for the independent variable. These two contrasting views appear in Figure 1(a) and (b).

Figure 1. Symmetrical and Asymmetrical Relationships between X and Y for 15 Cases of Synthetic Data



The asymmetric relationship in Figure 1(b) indicates that a high score in statement X associates with a high score in Y while acknowledging that Y can be high when X is low—other X recipes occur that result in high values for Y. An algorithm is judged to be useful only if the algorithm shows that high values in X associate with high values in Y.

While the use of algorithms occurs frequently in real-life decision-making (Woodside et al., 2012), their use is infrequent though highly valuable in scholarly reports (e.g., McClelland, 1998). Consequently, Section 2 describes the use of Boolean algebra-based software (fsQCA.com) for testing algorithms. The overarching objective is to encourage comparisons in thinking and data analyses using both algorithm and statistical tools.

Section 3 summarizes an unobtrusive field experiment where participants are not informed that they are participants in the study before, during, or after a treatment is administered. Section 4 presents traditional analysis and findings for the data from the experiment. Section 5 presents analyses using fsQCA. Section 6 is a discussion that compares the benefits and limitations of the two methods. Section 7 concludes with recommendations for advancing marketing theory and practice.

2. Stating and Testing Algorithm Models

The proposal that Boolean algebra and set theory are useful for describing algorithms of combinations of antecedent conditions that lead to a given outcome of interest relates to proposals of asymmetric relationships. Here is an example of an algorithm: the combination of low price (~price), shopping alone (~pal), and a highly expert sales message (E) results in a sale. (The tilde symbol, "~" represents the negation of the antecedent condition.)

Equations (1a) and (1b) are alternative ways of stating this algorithm (the mid-level dot ("●") represents the logical "and" relationship). Equation (1a) indicates that this Boolean algebraic model expresses that the combination of all three conditions is sufficient for a purchase to occur (not that this expression is a necessity just that its occurrence is sufficient for a purchase outcome).

$$\sim\text{price\_c}\bullet\sim\text{pal\_c}\bullet\text{expert\_c} \rightarrow \text{purchase\_c}. \tag{1a}$$

$$\sim\text{price\_c}\bullet\sim\text{pal\_c}\bullet\text{expert\_c} \leq \text{purchase\_c}. \tag{1b}$$

Both (1a) and (1b) indicate the same proposal: a high value in the conjunctive antecedent model, ~price_c●~pal_c●expert_c, leads to a high value in the outcome condition, that is, purchase. A customer shopping alone AND exposed to a low price AND receiving a highly expert sales message will buy the focal product. Equation (1b) states that high values of the antecedent combinatory statement, ~price_c●~pal_c●expert_c, are less than the high values of the outcome condition, purchase_c. The postscript "_c" indicates a calibrated score rather than an original value for a given condition. For the purchase condition, codes for the original data usually include 0.00 for non-purchase and 1.00 for purchase; the recommended (Fiss, 2009) calibrated codes for such dummy codes for purchase_c are 0.01 and 0.99—the fsQCA.com software performs better with this slight modification to the two scores rather than using the original dummy-coded scores. However, dummy codes of 0.00 and 1.00 often work well when using fsQCA.com and are used in the following examples in this paper.

Computationally, all conditions in (1a) or (1b), i.e., price, pal, expert, and purchase, are scores calibrated from original values—analogous to z transformations of original data using matrix algebra. "Condition" in algorithm analysis is analogous to "variable" in statistical analysis.

Calibration

Calibrated scores for use in Boolean algebra range for 0.00 to 1.00 (or 0.01 to 0.99 for older versions of the fsQCA.com software). If a specific price point is the highest for a range of prices, the price-point code would equal 0.99. Alternatively, the lowest price-point code would equal 0.01.

If "pal" represents a customer shopping with a friend, the calibrated score of this level of the condition, pal, equals 1.00. If high and low expert levels are used in a field experiment, the score for low expert would be 0.00 and the score for high expertise would be 1.00. Using Boolean algebra, the specific score for the combination of ~price_c●~pal_c●expert_c equals the lowest score appearing in this combination. Thus, for ~price_c = 0.00, ~pal_cl = 0.00, and expert_c = 1.00 the combination score equals 0.00.

In many studies, calibration of scores in fsQCA reflects the perspective that variation in data for a given condition varies in its information usefulness. For example, assume that you have ten countries with single letter names—A, B, C, D, E, F, G, H, I, and J—and that corresponding median household incomes (USD) are 500, 700, 800, 1,500, 3,000, 5,000, 7,000, 9,000, 14,000, and 22,000. The fsQCA calibration procedure asks the researcher to identify three membership points from theory and prior evidence that are necessary for the calibration: the threshold point indicating full non-membership in the condition (equal to 0.05); the cross-over point between non-membership and membership that indicates maximum ambiguity; and the threshold point indicating full membership in the condition.

If the condition is "high income countries" (hi_income_c) and the three points are defined by theory and prior evidence to equal 1,000, 4,000, and 10,000, then the calibrated scores for the ten countries are A = 0.03, B = 0.04, C = 0.04, D = 0.08, E = 0.27, F = 0.62, G = 0.82, H = 0.92, I = 0.99, J = 1.00. This calibration indicates that two countries (I and J) have full membership scores in the condition high income and three countries have full non-membership scores of being high income countries (A, B, and C). Calibration results in scores comparable across conditions and corrects for data values that distort information relevant for testing theory—discarding data that seem to represent "statistical outliers" does not occur in calibration and fsQCA.

The calibrated values for "not high income countries" (~hi_income_c) is the negation of these values; for example, for country A, ~hi_income_c = 0.97. Note that "low income" does not have the same meaning as "not high income" and the calibration for low income would not be equal to "not high income." Calibration for low income is not done here; Ragin (2008) and Woodside and Zhang (2013) provide additional details and examples on how to perform calibrations.

Assume a researcher has data for six cases of consumers shopping for a product that is being market tested at three price points: $1.98, $2.98; and $3.98. Table 1 shows hypothetical data for the six cases in a "thought experiment" (a "gedanken" in German, see Cohen, 2005).

Notice the details in Table 1. The first case (customer 1) is exposed to price-point $1.98 (i.e., price_c = 0.01 and ~price_c = 0.99) and she/he is shopping alone;

thus, pal_c = 0.00 and ~pal_c = 1.00. The first customer is exposed to an expert sales message; thus, expert_c = 1.00.

Table 1. Computation to Estimate Consistency for Six Cases

A Case	B Price	C Pal	D Expertise	E Purchase	F Price_c	G ~Price_c	H ~Pal_c	I Expertise_c	J ~Price_c●~Pal ●Expert_c	K Purchase_c	L Min((Ji,Ki))
1	$1.98	No	Yes	Yes	0.01	0.99	1.00	1.00	0.99	1.00	0.99
2	$1.98	No	No	No	0.01	0.99	0.00	0.00	0.00	0.00	0.00
3	$2.98	No	Yes	Yes	0.50	0.50	1.00	1.00	0.50	1.00	0.50
4	$2.98	Yes	Yes	Yes	0.50	0.50	0.00	1.00	0.00	1.00	0.00
5	$3.98	No	No	No	0.99	0.01	1.00	0.00	0.00	0.00	0.00
6	$3.98	Yes	No	Yes	0.99	0.01	0.00	1.00	0.00	1.00	0.00
7	Total								**1.49**	**4.00**	**1.49**

Consistency=Σmin(Ji, Ki)/ ΣJ=**1.49/1.49=1.00**

Coverage=Σmin(Ji, Ki)/ ΣK=**1.49/4.00=0.37**

Table 1 includes data for just one combinatory model: ~price_c●~pal_c●expert_c. The value for this model for case 1 equals 0.99●1.00●100; this value is equal to 0.99 remembering that the lowest value in this combination represents its Boolean conjunction. The data for case 1 indicates that the customer purchased the focal product (i.e., purchase_c = 1.00).

Index calculations for "consistency" and "coverage" appear in Table 1. According to Ragin (2008), set-theoretic ''consistency'' gauges the degree to which the cases sharing a given combination of conditions agree in displaying the outcome in question. That is, consistency indicates how closely a perfect subset relation of "whales" is approximated by a causal recipe of a configuration of antecedent conditions. Consistency is analogous to significance metrics (e.g., the sample correlation coefficient r) in statistical hypothesis testing. Ragin suggests that a configural model should achieve a consistency $\geq$ 0.80 to be useful, and the fsQCA.com permits testing for consistency of models beginning at 0.70.

The consistency computation in Table 1 indicates that the model works well. Even though only case 1 has a high membership score in this model, among the six cases when a case has a high model score, the outcome condition (purchase) indicates full membership (1.00). The numbers in Table 1 indicate membership scores and not original scaled values.

Table 1 includes purchases by four customers and non-purchases by two customers. The findings for the conjunctive model tested in Table 1 (~price_c●~pal_c●expert_c) indicates that this model is irrelevant in explaining the purchases by customers 3, 4, and 6. Additional conjunctive models of the same three simple antecedent conditions (i.e., price, pal, expert) may be useful for explaining purchase. In real-life, no one Boolean or matrix-based model is both sufficient and necessary usually for explaining an outcome condition. Two-to-ten models are likely to be informative explaining an outcome condition when five-to-ten antecedent conditions are under examination for combinatory influences on an outcome.

Consistency and Coverage

Consistency is an index that indicates the extent that scores for the simple or complex antecedent condition is lower than their corresponding outcome condition scores. Consistency is first in importance in interpretations in QCA; without relatively high consistency (≥ 0.75 or 0.80) the discussion of coverage is moot.

Set-theoretic ‘‘coverage’’ assesses the degree to which a cause or causal combination accounts for instances of an outcome. That is, analogous to goodness-of-fit “effect sizes” (e.g., the coefficient of determination adjusted R^2) in statistical hypothesis testing, coverage gauges empirical relevance or importance. Table 1 indicates the coverage for the model ~price_c●~pal_c●expert_c is 0.37. In particular, coverage results from 0.00 to 0.60 are intriguing. Theoretically, a model with high consistency and near zero coverage indicates a case that rarely occurs now but might be designed to occur because such a case associates with an outcome of particular interest (e.g., purchase in the context of marketing and positive-to-negative presence of a disease in the context of a medical treatment).

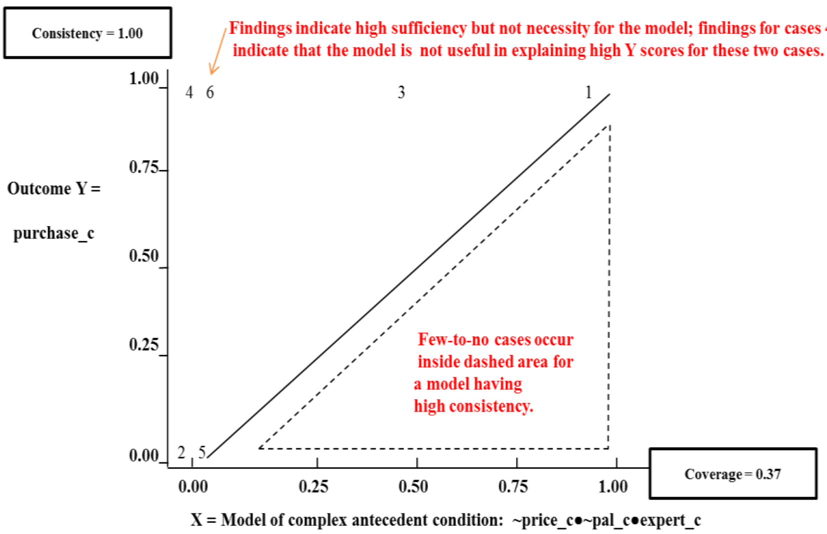
Visualizing Findings for Tests of Algorithms

Figure 2 is an X-Y plot of the findings for the consistency of the complex antecedent-condition model ~price_c●~pal_c●expert_c. Figure 2 shows that the model is consistent: high scores in the model associate with high scores in the outcome condition. Algorithm analysis makes no prediction about the relationship between Y and X for low scores for the complex antecedent-condition model. We conclude only that the model is useful for explaining high scores in Y and know that high scores in X are necessary for high scores in Y.

Unobtrusive Field Experimentation

Context matters. Simon (1990, p.7) famously proposed “Human rational behavior is shaped by a scissors whose two blades are the structure of the task environment and the computational capabilities of the actor.” This view applies to a context in which an experiment takes place—in a real-life field setting. Levitt and List (2007) provides relevant empirical evidence that human behavior varies substantially in field versus laboratory studies—humans are more cooperative and ethical in their behavior in laboratory contexts. While laboratory studies often provide useful information, their relevancy may be restricted to laboratory contexts while field experiments are likely to have greater relevancy to real-life context (e.g., List, 2006).

Figure 2. Visualizing the Findings for the Model ~Price_C●~Pal_C●Expert_C for the Synthetic Data



Notes: The X-axis is a conjunctive statement (i.e., a recipe) representing a complex condition that predicts high values of Y occur for high values of X; no prediction is made for low values of X. The findings for consistency (1.00) indicate that the model is useful. The findings for coverage (0.37) indicate that the model is representative of some of the cases.

A continuum is a useful way of viewing the obtrusiveness of a field experiment. Obtrusiveness can be very high if the procedure is a unique occurrence for the participants in the study. Here is an example of a highly obtrusive field experiment: Ehrenberg (1988) and assistants going to homes of participants for many weeks to ask household members to select one brand each from a tray containing three brands for each of four product categories—over the course of many weeks price levels and other conditions would be changed and the influences on these changes on purchases would be estimated.

The data for the present paper come from Woodside and Davenport (1974, 1976). The study procedure by Woodside and Davenport (1972, 1976) is very low in obtrusiveness: customers participating in the study were not informed before, during, or after of their participation. The context was as close to a natural occurrence as possible.

Theory

Theory Building from a Net Effects Perspective

From a net effects (empirical positivism statistical testing) perspective, the relevant theory that the field experiment examines includes the following hypotheses and rationales. The discussion here presents only hypotheses for demand; the hypotheses for profit are similar to the hypotheses for demand.

H1: Price increases cause decreases in demand. Price increases serve to reduce the inherent value/price relationship in the product-service perceived by the customer.

H2: A face-to-face expert versus non-expert communication by a salesperson causes demand to increase. Increases in expertise serve to increase the inherent value/price relationship in the product-service perceived by the customer.

H3: The decreases in demand due to price increases are less for high versus low expertise in the salesperson communication. The high expertise message serves to justify paying a high price for the product-service in the customer's mind.

H4: The presence of a friend or "shopping pal" versus no friend present causes a decrease in demand. The presence of a pal causes the focal shopper to think more rationally than the absence of a pal. The pal may remind the focal shopper that the original purpose of the shopping did not include buying the product-service or responding favorably to the salesperson's suggestion to buy the product-service. A quick note: the findings are opposite of H4's prediction.

H5: The presence of a pal versus no pal increases the negative impact of price increases on demand decreases. The presence of a pal prompts the focal shopper to recognize the low value/price ratio when price is high—the shopper is more vigilant about price in the pal present versus absent condition. The findings do not support H5; a hypothesis quite different from H5 receives support.

H6: The increase in demand due to the expert versus non-expert message is greater for the no-pal versus pal condition. The focal shopper relies on the likely negative view of the pal to counteract the impact on demand of the expert versus non-expert message. The findings do not support H6.

H7: A three-way interaction effect occurs: the decrease in the impact of price on demand for the expert versus no-expert condition is greatest when no pal is present versus when a pal is absent. Figure 3 is a visual of this three-way interaction. The findings do not support H7; findings opposite to H7 occurred in the field experiment reported below.

Theory Building from a Causal Recipe Perspective

In contrast to many studies that apply statistical modeling with hypotheses of optimal pricing and related management decisions (Shah, et al. 2012), the following propositions apply a causal recipe perspective of how antecedent conditions influence the score (low versus high) for an outcome condition (e.g., demand). No one simple condition such as price, expertise, or pal is sufficient for influencing demand. A combination of conditions is sufficient but not necessary for a high score in an outcome condition. Because causal recipes consider the impact of alternative ingredients in different recipes, proposals for optimality of any one condition (e.g., price) based on the net effect of the condition are non-applicable—decisions differ depending on context, and algorithms always include findings for multiple relevant contexts.

The following causal recipes are sufficient in that a high score in the recipe associates with a high score in the outcome condition:

$$\text{expert}\bullet\text{pal} \le \text{demand}. \tag{2}$$

$$\text{expert}\bullet\sim\text{price} \le \text{demand}. \tag{3}$$

$$\text{expert}\bullet\sim\text{pal}\bullet\sim\text{price} \le \text{demand}. \tag{4}$$

$$\sim\text{expert}\bullet\text{pal}\bullet\text{price} \le \sim\text{demand}. \tag{5}$$

Figure 2 shows an X-Y plot for sufficiency but not necessity recipes that would support (4). Equation (5) refers to the negation of demand, i.e., an equation proposed that results in low scores for demand—close to no customer buys for high scores for (5). While not appearing in (5) versus (4), causal asymmetry is often central to crafting theory using configural thinking; that is, the cause of not buying or failure include conditions in their recipes that differ from the conditions associating with buying or success.

3. The Unobtrusive Field Experiment

The study uses the data of an unobtrusive field experiment (Woodside and Davenport, 1972, 1976). The experiment was set in a retail store, and the product was the "HC-2001 Head and Capstan Cleaner kit," which was a novel product with somewhat complex technology at the time of the study and was considered to be important since tape players were popular music players during the age of the experiment. The kit includes two felts pads, head cleaning solutions, and a cartridge to be used to clean 8-track players. The product was only introduced to the market during the month of the experiment and none of the firm's six major competitors has the same kind of product to offer in time because of the relatively quick launch of the product by the firm.

The salesperson tried to induce the customers who just bought some tapes to consider buying the tape-cleaner kit; customers were assigned randomly to different treatment conditions. Each salesperson-customer exchange includes two treatment conditions: a salesperson expertise level and a price-point. Two salesperson expertise messages (expert versus non-expert) and four price-points ($1.98, $2.98, $3.98, $5.98) make the total of eight different treatment combinations. Thirty customers were assigned randomly to each of the eight combinations; thus, the total sample size of the study is 240 customers.

Data were also collected on whether or not the customers were shopping with or without someone else (a "measured" or "chronic" variable, the "pal" condition) when they were making the purchase decision. Since this antecedent is not manipulated in the experiment in each condition, the number of customers with or without a pal can range between 0 and 30.

The unobtrusive nature of the experiment is signified by the fact that the subjects were not informed as to the condition they were assigned, the salesperson did not know beforehand what price-message combination was to be applied next (a random set of instructions as to the message and price to apply next appeared on separate pages placed beneath the cash register), and the customers could not see any other possible prices or other expertise level except the only price on the 6x6-inch card in front of them when the salesperson introduced the product to them. The procedure occurred in a natural shopping setting. Further details of the unobtrusive field experiment procedures and experiment context appear in Woodside and Pitts (1974, 1976).

In this study, the antecedents include four prices, expertise and non-expert sales messages, and customers with and without pal conditions. To further the exploration of the initial study, the present study includes "profit" to the outcome in addition to "purchase" because profit is an important criterion to marketing response.

For the antecedents for expertise and pal, the calibration includes 0.00 and 1.00 because there are two scores available for each condition. For the antecedent price, the calibrated membership scores for each price in the study, price points of \$1.98, \$2.98, \$3.98, and \$5.98, are 0.05, 0.27, 0.74, and 0.96, respectively. For the outcome condition of the study, purchase is either 0.00 or 1.00; but for the high profit outcome set, the highest to the lowest profits possible include 4.98, 2.98, 1.98, 0.98, and 0.00; the calibrations for these profits are 0.99, 0.75, 0.50, 0.25, and 0.01.

Table 2 is a summary showing the calibrations (i.e., the scores for the specific points or levels of each condition). Two different calibration scales for profit appear in Table 2: an "exuberant profit" scoring scale and a "normal profit" scoring scale. The exuberant scale expresses the view numerically that profits are exceptionally high when the sale returns a profit twice the cost of the item that the retailer pays. Thus, a profit of \$1.98 for an item with a retail price of \$2.98 has calibrated profit score 0.78 for the exuberant scale but 0.50 for the normal scale. A gross profit is classifiable as exuberant when the profit to the retailer is \$1.98 on an item costing the retailer \$1.00 and the retailer's price is \$2.98 versus when the retailer's markup is typically 50% of the selling price or 100% of the retailer's cost.

Predictive Validity of the Data in the Experiment

This research tests for predictive validity of the models for both statistical analysis and QCA findings. The study includes partitioning the sample into two equal size datasets to test for predictive validity of the model based on the training sample using the data from the validation sample (and vice versa). The study randomly selects half of the data from each of the eight groups covering the 4 (prices) by 2 (expert levels) experiment. Note the difference from randomly selecting half from the whole sample data. This study examines the predictive validity to show the generalization of the MRA and fsQCA conclusion and also to call for predictive validity testing to be a routine in future research using MRA or fsQCA.

Table 2. Calibration for Price, Salesman Expertise, Purchase Pal, and Profit Conditions

Conditions		Calibration	
Price	$1.98	0.05	
	$2.98	0.27	
	$3.98	0.74	
	$5.98	0.96	
		Calibration (Exuberant)	Calibration (Normal)
Profit	$0	0.01	0.01
	$0.98	0.33	0.25
	$1.98	0.78	0.50
	$2.98	0.95	0.75
	$3.98	0.99	0.99
Expertise Calibration	Expertise	0.99	
	Non Expertise	0.01	
Purchase Pal Calibration	Pal	0.99	
	No Pal	0.01	
Purchase Calibration	Purchase	0.99	
	Not Purchase	0.01	

Notes: 1. The calibrations of prices $1.98, $3.47, and $4.95 are for full non-membership threshold, crossover point, and full membership threshold of 0.05, 0.50, and 0.95 in fsQCA, respectively. 2. The calibration for exuberant profits $0.05, $1.26, $2.98 are for full non-membership threshold, crossover point, and full membership threshold of 0.05, 0.50, and 0.95 in fsQCA, respectively. 3. The calibration for normal profits used a five-value fuzzy-set calibration. 4. The calibrations for expertise, purchase pal, and purchase are crisp set values.

4. Findings for Empirical Positivistic Analysis

The data in Table 3 include all the data points necessary to convert the information into a data file for statistical analysis (e.g., using SPSS or SAS) and qualitative comparative analysis (using fsQCA). Data for the control group that appear in Table 3 were not used in the analysis in this paper.

Findings from the Statistical Analysis

Figures 3 and 4 are visualizations of key findings. No statistical analyses are necessary for concluding that the findings do not support H1 for a wide range of prices. Price does not influence demand over the first three price points in the experiment. Demand does decline dramatically for the $5.98 versus the $3.98 price. A price-demand tipping point occurs for a price at some point greater than the suggested retail price of $1.98.

Table 3. Customer Purchase Behavior for Four Price, Two Salesman Expertise, and Two Purchase Pal Conditions

Price	Salesman Expertise	Purchase Pal	Purchase	No Purchase	n
$1.98	Expert	Yes	13	2	15
		No	11	4	15
	Non Expert	Yes	5	7	12
		No	4	14	18
$2.98	Expert	Yes	9	0	9
		No	12	9	21
	Non Expert	Yes	6	6	12
		No	5	13	18
$3.98	Expert	Yes	12	1	13
		No	8	9	17
	Non Expert	Yes	3	3	6
		No	9	15	24
$5.98	Expert	Yes	2	4	6
		No	2	22	24
	Non Expert	Yes	1	9	10
		No	0	20	20
$1.98	Control		4	26	30

Looking at Figure 3, no statistical analysis is necessary for concluding that the findings support H2: 65 units were sold for the 90 high-expertise executions versus 32 units sold for the 90 low-expertise executions across the first three price levels. Sales doubled for the high versus low expertise conditions. Unit sales were very low for both message conditions at the $5.98 price even though sales were four times greater (4 units) for the high expertise versus low expertise levels at this extreme price.

The findings in Figure 3 do not support H3. A small sales decline occurs as price increased from $1.98 to $3.98 for the expert message condition but sales increased versus declined for the low expert condition—but the increase was only from 9 to 12 units. Clearly, the pattern of these findings does not support H3.

Figure 4 illustrates findings relevant for testing H4. The findings do not support H4: sales did not decline with the presence of a purchase pal; sales increased with the presence of a purchase pal. Typically, sales occurred 75% of the times when a pal was present versus 43%percent of the times when a pal was absent—a finding supporting a hypothesis opposite that of H4.

The three interaction hypotheses (H5–H7) do not receive support since the pal condition resulted in higher sales than the no pal condition—findings opposite of expectations. Possibly the focal customer was exhibiting conspicuous purchasing behavior in the pal condition and did not need to explain the decision not to buy in the no pal condition. The explanation to the counter-intuitive findings for pal awaits additional research.

Figure 3. Effects of Price and Salesman Expertise

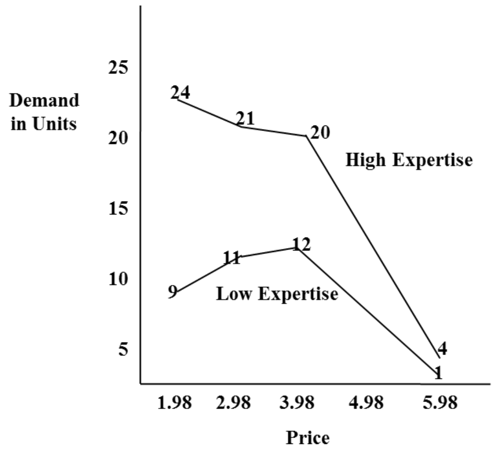
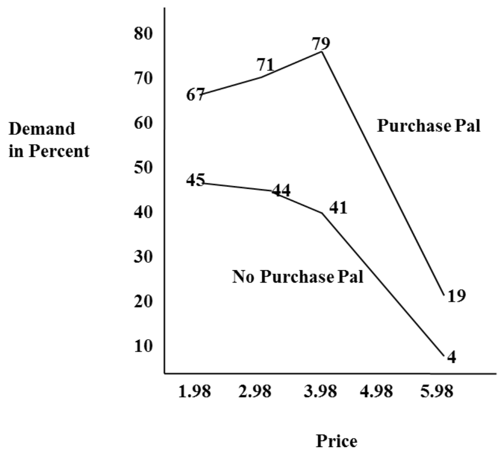


Figure 4. Effects of Price and Price and Purchase Pal



Statistical Analysis

Table 4 includes MRA findings for unit demand and profit using a quadratic function for price and expertise and pal conditions. The findings are similar for both unit demand and profits; all terms in the two equations are significant. Price has a positive and then a negative impact on unit sales and profit. Expertise has a positive impact on unit sales and profit. Pal has a positive (not a negative) impact on unit sales and profit.

Table 4. Multiple Regression Models Predicting Purchase and Profit Using All Data (N=240)

Purchase

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.551[a]	.304	.292	.40843

a. Predictors: (Constant), pal, experise, price2, price

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	17.125	4	4.281	25.665	.000[b]
	Residual	39.202	235	.167		
	Total	56.327	239			

a. Dependent Variable: purchase

b. Predictors: (Constant), pal, experise, price2, price

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.123	.227		-.542	.589
	price	.303	.122	.925	2.482	.014
	price2	-.051	.015	-1.264	-3.394	.001
	experise	.294	.054	.297	5.460	.000
	pal	.246	.057	.237	4.304	.000

a. Dependent Variable: purchase

Profit

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.497[a]	.247	.234	1.08684

a. Predictors: (Constant), pal, experise, price2, price

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	90.930	4	22.733	19.245	.000[b]
	Residual	277.585	235	1.181		
	Total	368.515	239			

a. Dependent Variable: profit

b. Predictors: (Constant), pal, experise, price2, price

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-3.205	.603		-5.313	.000
	price	2.082	.325	2.484	6.408	.000
	price2	-.259	.040	-2.534	-6.544	.000
	experise	.604	.143	.239	4.220	.000
	pal	.625	.152	.235	4.112	.000

a. Dependent Variable: profit

Table 5. Findings for <u>Purchase</u> Models for Two Sub-Samples (N=120 for Each Sub-Sample) Showing the Fit Validities and Cross-Validation (Predictive Validity)

Sub-Sample A

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.614	.440		-1.395	.166
	price	.690	.269	1.582	2.560	.012
	price2	-.116	.038	-1.874	-3.035	.003
	expertise	.254	.078	.255	3.234	.002
	pal	.262	.083	.252	3.163	.002

a. Dependent Variable: purchase

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8.208	4	2.052	11.616	.000[b]
	Residual	20.315	115	.177		
	Total	28.524	119			

a. Dependent Variable: purchase

b. Predictors: (Constant), pal, expertise, price2, price

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.536[a]	.288	.263	.42030

a. Predictors: (Constant), pal, expertise, price2, price

Sub-Sample B

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.513	.428		-1.199	.233
	price	.583	.262	1.359	2.230	.028
	price2	-.102	.037	-1.663	-2.732	.007
	expertise	.333	.076	.340	4.387	.000
	pal	.232	.081	.223	2.854	.005

a. Dependent Variable: purchase

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8.532	4	2.133	12.824	.000[b]
	Residual	19.127	115	.166		
	Total	27.660	119			

a. Dependent Variable: purchase

b. Predictors: (Constant), pal, expertise, price2, price

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.555[a]	.308	.284	.40783

a. Predictors: (Constant), pal, expertise, price2, price

Notes.

1. Purchase_A = -.614+(.690*price)-(.116*price2)+(.254*expertise)+(.262*pal); purchase_B = -.513+(.583 * price)-(.102*price2)+(.333*expertise)+(.232*pal).
2. Fit validity for purchase A using model A : r = .536; fit validity for purchase B using model B: r = .555.
3. Predictive validity of the model B to estimate purchase _A: r = .530; predictive validity for model A to estimate purchase _B : r= .548.

Table 6. Findings for <u>Profit</u> Models for Two Sub-Samples (N=120 for Each Sub-Sample) Showing the Fit Validities and Cross-Validation (Predictive Validity)

Sub-Sample A

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-4.779	1.116		-4.283	.000
	price	3.310	.683	3.073	4.846	.000
	price2	-.468	.097	-3.052	-4.814	.000
	expertise	.470	.199	.191	2.366	.020
	pal	.634	.210	.247	3.025	.003

a. Dependent Variable: profit

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	43.411	4	10.853	9.560	.000[b]
	Residual	130.554	115	1.135		
	Total	173.965	119			

a. Dependent Variable: profit

b. Predictors: (Constant), pal, expertise, price2, price

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.500[a]	.250	.223	1.06548

a. Predictors: (Constant), pal, expertise, price2, price

Sub-Sample B

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-4.405	1.048		-4.204	.000
	price	3.005	.641	2.929	4.689	.000
	price2	-.431	.091	-2.950	-4.725	.000
	expertise	.687	.186	.294	3.692	.000
	pal	.562	.199	.226	2.821	.006

a. Dependent Variable: profit

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	43.014	4	10.754	10.775	.000[b]
	Residual	114.773	115	.998		
	Total	157.787	119			

a. Dependent Variable: profit

b. Predictors: (Constant), pal, expertise, price2, price

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.522[a]	.273	.247	.99901

a. Predictors: (Constant), pal, expertise, price2, price

Notes.

1. Profit model A = -4.779+(3.310*price)-(.468*price2)+(.470*expertise)+(.634*pal); profit model B = -4.405+(3.005*price)-(.431*price2)+(.687*expertise)+(.562*pal).
2. Fit validity of model A to estimate sample A profit: r = .500; fit validity of model B to estimate sample B profit: r = .522.
3. Predictive validity of model A to estimate sample B profit: r = .510; predictive validity of model B to estimate sample A profit: r = .489.

Predictive Validity

The footnotes to Tables 5 and 6 provide estimates of fit and predictive validities for the MRA models for unit demand and profit respectively. Both fit and predictive validities are "large" (Cohen, 1977) for both unit demand and profit models ($r \geq 0.50$).

Table 7 presents cross-tabulations for examining tests of main effects for expertise, price, and pal on unit sales. The findings support the conclusions that pal and expertise have large effects on sales and price does not for a wide range of prices.

5. Findings from the fsQCA

The study includes creating fuzzy truth table algorithms in order to calculate configural findings. This algorithm calculates all alternative sufficient and necessary conditions that lead to the outcome. Once conditions are put in and the outcome is specified, the algorithms will both consider and examine the relevant condition combinations, including negation, for one or more of the simple conditions that lead to high consistency for the outcome condition. We have coded the algorithm to show recipes with a minimum consistency requirement of 0.7. Algorithms were run to show recipes for several outcomes in the following discussion.

Table 7.

A. Purchase by Price and Expertise

price * purchase * expertise Crosstabulation

expertise				purchase .01	purchase .99	Total
.01	price	.05	Count	21	9	30
			% within price	70.0%	30.0%	100.0%
		.27	Count	19	11	30
Low Expertise			% within price	63.3%	36.7%	100.0%
		.74	Count	18	12	30
			% within price	60.0%	40.0%	100.0%
		.96	Count	29	1	30
			% within price	96.7%	3.3%	100.0%
	Total		Count	87	33	120
			% within price	72.5%	27.5%	100.0%
.99	price	.05	Count	6	24	30
			% within price	20.0%	80.0%	100.0%
		.27	Count	9	21	30
High Expertise			% within price	30.0%	70.0%	100.0%
		.74	Count	10	20	30
			% within price	33.3%	66.7%	100.0%
		.96	Count	26	4	30
			% within price	86.7%	13.3%	100.0%
	Total		Count	51	69	120
			% within price	42.5%	57.5%	100.0%
Total	price	.05	Count	27	33	60
			% within price	45.0%	55.0%	100.0%
		.27	Count	28	32	60
			% within price	46.7%	53.3%	100.0%
		.74	Count	28	32	60
			% within price	46.7%	53.3%	100.0%
		.96	Count	55	5	60
			% within price	91.7%	8.3%	100.0%
	Total		Count	138	102	240
			% within price	57.5%	42.5%	100.0%

phi = 0.323, p < 0.006

B. Purchase by Price and Pal

price * purchase * pal Crosstabulation

pal				purchase .01	purchase .99	Total
.01	price	.05	Count	18	15	33
			% within price	54.5%	45.5%	100.0%
		.27	Count	22	17	39
			% within price	56.4%	43.6%	100.0%
No pal		.74	Count	24	17	41
			% within price	58.5%	41.5%	100.0%
		.96	Count	42	2	44
			% within price	95.5%	4.5%	100.0%
	Total		Count	106	51	157
			% within price	67.5%	32.5%	100.0%
.99	price	.05	Count	9	18	27
			% within price	33.3%	66.7%	100.0%
		.27	Count	6	15	21
			% within price	28.6%	71.4%	100.0%
Pal		.74	Count	4	15	19
			% within price	21.1%	78.9%	100.0%
		.96	Count	13	3	16
			% within price	81.2%	18.8%	100.0%
	Total		Count	32	51	83
			% within price	38.6%	61.4%	100.0%
Total	price	.05	Count	27	33	60
			% within price	45.0%	55.0%	100.0%
		.27	Count	28	32	60
			% within price	46.7%	53.3%	100.0%
		.74	Count	28	32	60
			% within price	46.7%	53.3%	100.0%
		.96	Count	55	5	60
			% within price	91.7%	8.3%	100.0%
	Total		Count	138	102	240
			% within price	57.5%	42.5%	100.0%

phi = 0.373, p <.000

Notes. 1. Rounded rectangular indicates highest and ovals indicates lowest share purchases.
2. Purchase share is highest for high versus low expertise and pal versus no pal for each of the four prices.

Purchase is the first outcome run. The algorithm calculated that the recipe of expertise●pal●leads to purchase; this recipe is the only sufficient condition that leads to high consistency for the purchase outcome. Regardless of the price level, having an expert AND a pal is sufficient to achieve the outcome of a purchase. The consistency for this recipe is 0.845 and the unique coverage is 0.368.

Not purchase (~purchase) was the next outcome that was run. The algorithm calculated that three recipes are sufficient to lead to the outcome of not purchase: ~expertise●~pal + ~pal●price + ~expertise●price with plus sign ("+") indicating the logical "or" condition. Since QCA is an asymmetric rather than symmetric tool, we do not deduce that the opposite of these recipes will lead to a purchase. Rather, causal asymmetry holds and any of these recipes lead to a non-purchase. See Figure 6 for two examples of non-purchase models; panel A represents price and not expertise and panel B represents not pal and not expertise.

The next outcome is “exuberant” profit. The algorithm calculated that only the recipe of experitise●pal●price is sufficient to lead to the outcome of high consistency for exuberant profit. The consistency for this recipe is 0.775 and the coverage is 0.292.

The next outcome is ~exuberant profit. The algorithm calculated that two recipes are sufficient to lead to the outcome of not exuberant profit: ~expertise + ~pal. This finding shows that it does not matter what the price level is, not having an expert or not having a pal is sufficient to lead to not making exuberant profit. The solution consistency is 0.745 and the solution coverage is 0.892.

Predictive Validity of the fsQCA Models

Figure 5 includes findings for testing the model pal●expertise → purchase for two subsamples of the data (n = 120 for each sample with 15 cases from each of the 8 cells in each subsample). The models perform with high consistency (> 0.83) and substantial coverage (> 0.36) for each model. These findings support the conclusion that the model has acceptable predictive validity.

Figure 5a.
Sample 1, N=120: Pal●Expert≤ Purchase

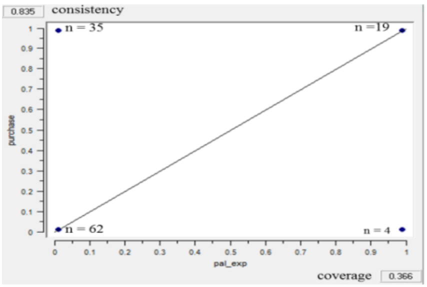
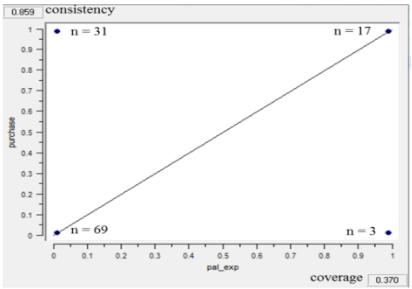


Figure 5b.
Sample 2, N=120: Pal●Expert≤ Purchase

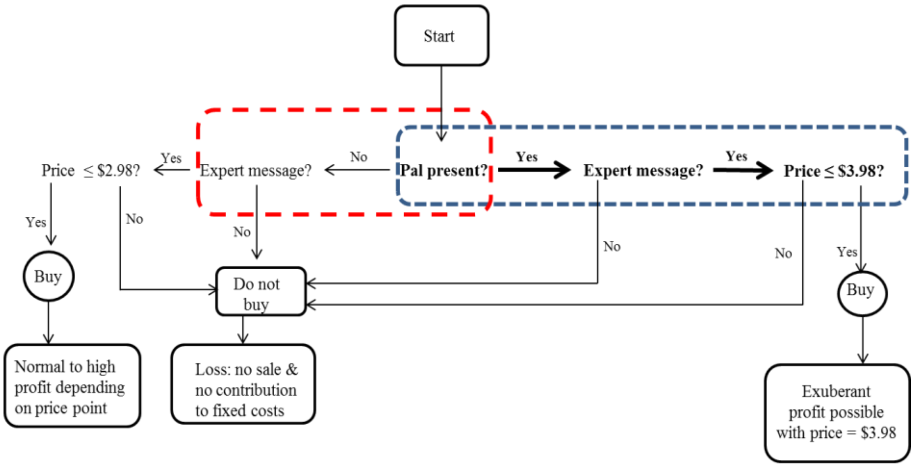


Notes: Figures illustrate test results for predictive validity of the pal●expert → purchase.

Figure 6 is a composite model of happenings (purchase versus non-purchase for the majority of outcomes for given combinations of price, expertise, and pal conditions. Figure 6 serves as a helpful visualization of the most profitable key success path (KSP) for the retailer to apply (when possible). For highest profit, if the customer enters the context (i.e., comes to the cash register and salesperson) with a pal, the salesperson should execute the expert sales message and price the tape cleaner at $3.98. For highest profit, if the customer does not bring a pal to the context, the salesperson should execute the expert sales message and price the tape cleaner at $2.98.

Figure 6 is representative of how managers might actually think—an isomorphic (i.e., in this instance, high correspondence with actual thinking processes) model that uses beliefs, evidence, and emotions that lead to a decision (Woodside et al., 2012; Woodside et al., 2012). A price point that a manager selects should depend on a specific set of contextual conditions. "Depend" implies "what if" analysis and modeling processes that isomorphic models capture.

Figure 6. Isomorphic-Management Model of Outcomes for Purchase and Non-Purchase Above 50% for 16 Configurations of 4 Prices by 2 Expertise and 2 Pal Conditions



Notes: Most profitable process for firm appears in **bold blue** dashed area; least profitable process for firm appears inside **bold red** dashed area. Products will not sell when ~pal●~expert.

Note in Figure 6 that no one factor (i.e., antecedent condition) is sufficient of for highest profit. Key success factors (KSFs) do not exist; in isolation, there are no KSFs. In real-life only KSPs occur. Crafting and presenting findings in an isomorphic model such as Figure 6 completes the SAIM process configural research that includes statistical, algorithm, and isomorphic-management modeling.

6. Comparing the Benefits and Limitations of the Two Methods

Being able to predict point estimates for the dependent variable is one benefit from applying MRA to data from field experiments. Given that a model has high fit validity, the second step should be taken to see if such predictions are accurate—by testing for predictive validity via a second sample of data. A model may provide acceptable fit validity and do poorly at providing acceptable predictive validity, as Gigerenzer and Brighton (2009) and Woodside (2013) demonstrate.

MRA provides useful information on whether or not the net effects of dependent variables and their interactions are significant statistically. However, sometimes the focus on significance of main and interactive effects and the relative sizes of these effects—by comparing the sizes of standardized partial regression coefficients (βs)—takes eyes away from the central issue: is the model accurate in predicting sought-after values in the dependent variables (purchase and profit). Prediction here refers to a high coefficient of determination (adjusted R^2) for the model applied to a validation sample.

The predictive validities ("effect sizes") for purchase and profit are "large" (Cohen, 1977), as the findings in Tables 5 and 6 indicate. Effect sizes almost never exceed r = 0.60 or R^2 = 0.36 for predicting the dependent variable in field experiments because MRA provides symmetrical estimates; that is, the tool predicts low and high values for the dependent variable. QCA and fsQCA do not.

Qualitative comparative analyses provide algorithms that predict high scores for an outcome condition (e.g., purchase or profit) without making any predictions about low scores for this outcome condition. For most relationships of theoretical interest that go beyond testing the obvious, correlations between two variables top-out at about 0.60 because relationships are asymmetrical rather than symmetrical. Writing questions to test the same construct that achieve coefficient alpha (r values) above 0.80 are an exception to this fact.

Reality most often includes several configurations of complex antecedent conditions whereby high scores in these conditions result in high scores in the outcome condition. Researchers should not think or craft theory in terms of "key success factors" because cases that do not fit the significant main effect between two variables always exist if the data sample is reasonably large (e.g., n > 300). The real issue needs to be and can be how to provide generalizations that account for nearly all the cases in a data set that have high scores for the outcome condition. Such generalization is achievable by crafting and testing alternative theories of complex configurations of antecedent conditions—"key success paths" and not key success factors.

No one factor is necessary or sufficient for a high score in an outcome condition. Even a supplier's fine reputation is insufficient for a supermarket buying committee to adopt a new product manufactured by this supplier (see Montgomery, 1975). This statement does not apply to low scores in an outcome condition.

A low score on some specific simple (often unexpected) antecedent conditions can prevent a high score on an outcome condition from occurring. To illustrate, Woodside and Baxter (2012) apply Van Maanen (1978) findings for the "asshole" in police work—the asshole is a certain type of street criminal—to industrial marketing-buying behavior. Woodside and Baxter (2012) report that being an asshole can prevent a buyer from becoming preferred customer no matter how favorable other ingredients appear in a complex antecedent condition. The key point here: causality is asymmetrical. The negation of what accounts for a key success path is not the negative scores for each of antecedents in the original key success path.

A researcher needs to treat negative outcomes (e.g., not buying and not profit) as outcomes distinct from positive outcomes. The study of failure is a field for theory and research unto itself and not the negation of the study of success. Thus, for example, Weick and Sutcliffe (2001) direct attention to the study of failures and propose tenets for the highly reliable organization. The tenets include five advocacies: preoccupation with failure, reluctance to simplify interpretations, sensitivity to operations, commitment to resilience, and deference to expertise.

Similarly, for the study at hand, attention to failure indicates that coupling not expertise when a customer shops alone (~pal●~expertise) associates with a high score on failure. However, other paths lead to high failure such as coupling high price with low expertise (price●~expertise)—thus, telling us not to simplify interpretations. To address sensitivity to operations, coupling a moderately high price with high expertise is likely to avoid failure. For commitment to resilience: Has the retailer tried every combination of expertise with the two pal conditions and four price points? Representing deference to expertise, the field experiment provides useful knowledge about the paths to desirable outcomes as well as the paths to undesirable outcomes.

7. Limitations, Conclusions, and Recommendations

Though others call for comparison of theory, findings, and interpretations in the same study via MRA and QCA, this study here and Woodside and Zhang's (2013) comparisons of QCA with MRA theory-method reports in Henrich (2010) may be the only two studies to do so. The number of available comparisons is a limitation for drawing firm conclusions.

However, the evidence and interpretations support extending Wagemann and Schneider's (2007, p. 17) observation that "QCA should not be applied as the only data analysis technique in a research project." Thus, MRA should not be applied as the only data analysis technique in a research project. Researchers should take to heart Ragin's (1997, 2010) insights in crafting theory and in analyzing data at the case-based level: his main insight is that QCA permits generalizing beyond the individual case while at the same time observing the relevancy of each conjunctive statement (recipe) for each individual case while discussions of findings and theory at the individual case level are set aside and ignored in most studies using MRA only.

QCA is more than just a tool; the same applies in studies using MRA. Gigerenzer's (1991, p. 19) claim is worth repeating: "Scientists' tools are not neutral." This work, in revisiting and extending the analyses of the data appearing in Woodside and Pitts (1976), provides credence to Gigerenzer's claim.

Both MRA and QCA include benefits and limitations. Fortunately, the benefits and limitations of ways of thinking and analyzing data are distinct for each so that using both approaches extends the benefits of each and overcomes several limitations. The hope is that this paper confirms this observation. The benefits of modeling and generalizing beyond the individual case when maintaining a study's focus on the individual case is do-able—an exceptional benefit for acquiring skills for crafting theory and analyzing data via configural comparative methods such as fsQCA.

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