

THE SUPERIORITY OF PANEL RESEARCH

A FAST FOOD CHOICE MODELING CASE STUDY USING ONLINE PANEL RESEARCH

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INTRODUCTION

Clients demand validity from researchers! We are seeing a global initiative to ensure that quality standards are developed for online research. The ARF has launched an Online Research Quality Control Council and there is an ISO initiative in this area, with support and involvement internationally.

At a specific level, this paper provides focus on online panels on matters of geographic reach, experimental methods and data integrity.

Online panel and face-to-face methodologies allow for valid replication of the research context of *real world* trade-off purchasing environments. However, *only online panels* provide this cost effectively, with optimal efficiencies enabling its wider use by both researchers and clients alike. This is because online panel research enables the use of increasingly sophisticated research techniques to provide the client optimized competitive insights, by integrating the research with the relative client pricing and metrics. More and more clients now find that research can have higher impact on marketing strategy by using advanced experimental techniques that are becoming increasingly accessible with the online medium. Researchers can therefore upgrade their deliverables and involvement in the client's business, by providing more actionable data for complex decisions.

Discrete choice experiments are well suited to on-line panels. The ease of presenting respondents with visual

choice tasks, coupled with the ability to manage quality controls, such as quota controls, or time stamping, are just two examples of the benefits derived from panel research, when compared to CATI, CAPI or paper-based survey methods. Other examples of the benefits offered by online panels are the cost efficiencies found in large samples; the ability to tailor discrete target groups; the geographic reach to non-metro or fringe communities; and the zero tolerance for human data management error, to mention just a few.

Online panels also offer both client and researcher the ability to transfer experimental results to a decision support system (DSS), i.e. a simulator. This provides the client with the opportunity to manipulate the DSS via *what-if* scenarios based on Microsoft Excel spreadsheets. More sophisticated DSSs use advanced graphics to make end user interaction even more accessible, by making the DSS appear less complex than those based on Microsoft Excel. In this case study, the client was provided two DSSs, one for modeling lunch trade, and the other dinner trade.

The challenge for this study was in designing an experiment capable of incorporating eight mutually exclusive meals with interlocking choices, and anchoring these to real purchase behavior (stated preferences, commonly referred to as SP data). We based our case study on a recent AMR Interactive market research initiative in Australia's fast food industry. Our aim was to provide solutions for the client's objectives of optimal pricing;

optimal meal structures; optimal meal combinations; and the separation of lunch to dinner sales for the purposes of profit forecasting. Client permission was received to present this material on a de-identified basis. This paper looks at the design, analysis, weighting and outputs of our case study. We begin our paper with an expanded discussion of online methodology.

BENEFITS OF ONLINE PANELS

Sample

In Australia, penetration of internet access is now in excess of 70%. Online panels are therefore relatively unconstrained by geography, which is made possible due to the internet and to the increased adoption of computers in the home and in the workplace. The increasing adoption of computer technology, commensurate with increased demand for faster download speeds from internet connection providers, means respondents find it easier to participate in marketing research via online than in the past.

As geographic reach is therefore no longer a problem, respondents can “log on” at any location, provided they can access the internet from either a public or personal computer. This ease of accessibility is unique to online panels, because alternative mediums of data solicitation are limited in reach, except where client funding is not an issue. The issue relating to the representativeness of on-line panels to the population, can be addressed by appropriate weighting procedures. This includes weighting by multiple panel membership, using a non-parametric model.

Design

Online research is also well suited to discrete choice experiments, which expose respondents to choice tasks

that are based on experimental designs. Experimental designs typically account for the number of choice alternatives, which represent the number of attributes and levels that need to be tested. To illustrate the complexity of an experimental design used in a discrete choice experiment, suppose there were three alternatives to choose from in a choice task, each item comprising three attributes {a, b, c}, each attribute containing three levels. Such a choice experiment would require 19,683 choice tasks based on a L^{MA} design (Louviere et al. 2000), to enable the estimation of all effects (table 1). Naturally, the researcher would seek a less overwhelming set of tasks to show the respondent, and this could be achieved by using fractional factorials based on an optimal configuration. Optimal experimental designs optimize the amount and quality of information the analyst can retrieve, whilst maximizing the degree of differences in the alternatives presented to respondents and keeping the number of tasks to a minimum (Street and Burgess, 2007). However, even though the number of choice tasks may decrease as a result of the researcher’s quest to simplify the experimental tasks, a degree of complexity nonetheless remains in presenting respondents their discrete choice tasks due to the repetitive nature of discrete choice methods.

Online experimental methods provide a visual medium where the researcher can simplify the complexity of combinations presented in a task. Visual information is presented to respondents in a systematic modularized fashion, allowing respondents to quickly understand the task. As respondents click through the choice tasks, they easily notice the changes from one task to another, thereby enabling the immediate appreciation of changes from one frame to another. Respondents are therefore able to trade off attributes against each other

**TABLE 1
EXAMPLE OF A CHOICE FRAME, ONE OF 19,683 COMBINATIONS**

Attributes	Brand _A	Brand _B	Brand _C
A	1	3	2
B	2	1	3
C	3	2	1

with relative ease. Such a degree of visual dexterity can only be gained via online research, as any other form of presenting such complex data requires continual reframing by the respondent, thereby reducing the clarity and hence the reliability by which a respondent can assess each choice task.

Data management in gathering the respondent's choices is also another issue easily dealt with by online research. As the respondent navigates through each choice task and decides on the alternative providing the highest utility, each decision is immediately captured electronically. Indeed, each choice task may call for more than one decision, such as when the choice task involves choosing the "best" alternative, then "second best", "third best" and so forth. The task may also call for a "choose none" option. As might be appreciated, the complexity of data capture increases with the number of choice tasks and decisions to be made within each choice set. Due to the ability of online to easily capture such choice information without human intervention in the data collection process, the quality of the data management process is both simplified and optimized when compared to manual handling of response data.

Yet another benefit of online panels may be found in controlling for quotas. Quota control has plagued marketing research for fear of introducing bias due to extraordinary attempts to fill quota strata. Quota control becomes an issue when there are sampling strata that are slow to fill, oftentimes inviting respondents that require either increased incentives, or increased frequency of reminders. The increased attention to these respondent means that the efficacy of data collection is exposed to risk, in that respondents for certain quota cells, who might otherwise have not participated in the study, decide to do so by the additional prompts and incentives thereby potentially increasing response bias.

Online panels avoid these pitfalls and offer optimal quota control. One reason is that panelists are pre-screened to a strict set of stratified and predefined criteria, to increase quality and representativeness. During an online panel study, the online panel quota control process is

executed by a programmed sequence, which adjusts sampling strata fulfillment on an on-going basis. Studies which are not conducted online can only make sampling adjustments in a lagged manner, as the reconciliation process to enable the monitoring of sample progress requires periodic or lagged counts to be taken. The questionnaire design can also accommodate the need for weighting variables, in particular multiple panel membership.

CASE STUDY: A FAST FOOD DISCRETE CHOICE STUDY USING ONLINE PANEL RESEARCH

Introduction

This paper reports on a study using online panel data that was conducted for a market participant in the fast food industry. As discussed, the purpose of the client's study was to provide insights into optimal pricing, meal bundles, and preference differences between lunch and evening trade. Also, the client wished to understand retention and churn forecasts, based on simulations and how potential price changes in the menu might expose the offering to cannibalization within the existing menu offering.

The challenge for the study was in designing an experiment capable of incorporating eight mutually exclusive meals, with interlocking choices, and anchoring these to real purchase behavior.

Design of the study

Sample

Geographic coverage was not an issue for this study, as we were using online research via the Online Research Unit (ORU) panel. The panel comprised over 400,000 respondents. Respondents were invited to participate in the study via email, wherein a web-link directed respondents to the discrete choice experiment hosted on our servers.

As the online panel had extensive representation of all quota strata, sample strata were easily filled. The randomization of strata fulfillment also promoted a bias-free solicitation process. Fieldwork was carried out over

a two-week period, to ensure full representation of the target groups. The client’s customers were screened for recent purchase, meal occasion, demographics and in-restaurant or drive-through purchase.

Design of the experiment

The discrete choice experiment was premised on an experimental design, which allowed for a systematic combinatorial manipulation of alternatives, attributes and levels.

In order to accommodate the complexity of client requirements in a systematic manner, the discrete choice experiment was based on an optimally efficient experimental design (Street and Burgess, 2007). One of the features we seek in optimally efficient designs is to present choice tasks that vary the alternatives in the maximum way possible, so that respondents are encouraged to consider all alternatives, not just those that change between choice sets.

Respondents were provided blocks of 16 choice sets based on a fractional factorial design, small enough for respondents to comfortably undertake, and large enough to enable the estimation of un-confounded main effects, second order interactions and cross

effects. Respondents were asked to trade off between features and feature levels, to arrive at a choice between alternatives in each choice task.

1. Validity

To ensure the validity of the experiment we made the tasks as realistic as possible, by including the last respondent’s meal and its market price at the time of purchase. This information was collected during the screening process.

The purpose of using the last meal and price paid for each individual in the experiment was to ensure the trade-offs for each hypothetical scenario forced the respondent to a real market situation, thus making it a realistic choice task as possible.

2. Managing and simplifying the choice task Figure 1 demonstrates one of the choice tasks (de-identified) the respondents were asked to make a choice from. Respondents were presented with their last meal purchased and the price most likely paid. Respondents were then asked to make a choice from the available options. If they found none of these appealing, they were asked to choose the option “same as last purchase”. (See figure 1.)

**FIGURE 1
EXAMPLE OF A CHOICE SCENARIO**

Scenario Number: Example of the choices tasks	
You last purchased	Price you most likely paid
Meal Type _x	\$24.50
Menu items in scenario	Potential new menu prices
Meal _A	\$25.70
Meal _B	\$27.60
Meal _C	\$25.70
Meal _D	\$17.30
When you last visited <Client>, if the menu item’s prices were as shown, would you have chosen the same meal component you did then, or would you have made a different choice?	
<input type="radio"/> Same as last purchase <input type="radio"/> Meal _A <input type="radio"/> Meal _B <input type="radio"/> Meal _C <input type="radio"/> Meal _D	

PART 2 / DATA QUALITY

The choice tasks were presented in a manner that was visually easy to understand. As discussed, the meal last purchased and the price most likely paid clearly led the respondent to the trade-offs we intended them to undergo.

Respondents were asked to evaluate hypothetical menu product alternatives, and to choose their most preferred option. Choice task alternatives comprised a base price indicating the respondent’s most recent in-market purchase, i.e. their revealed preference (RP), against a hypothetical set of alternatives from which preferences were recorded.

As the respondent’s most recent meal occasion was collected during the screening process, the purpose was to classify each respondent into a meal occasion category, so the respondent would receive the appropriate choice sets pertaining to their most recent in-market meal occasion. This live classification process categorized respondents into predefined strata of dining occasion, such as lunch or dinner, based on their RP purpose for their last visit to the client’s restaurant. The speed and efficiency at which such classifications were made is only available via online research. Face to face and CATI data collection methodologies are indeed capable of conducting concurrent screening and allotment process in real time. Face to face and CATI methods require staggered or lagged process management, and as such cannot be completed in a single session survey totaling 15-20 minutes. Table 2 provides an illustration of the segments respondents were assigned to during the online study, acting as a quota control and a balanced random allotment of respondents across categorized choice sets.

The method of combining RP and SP data in the final DSS enables the simulation of real market behavior. Although respondents may not successfully recall the price of their most recent in-market purchase, they will in most instances recall the actual menu item they consumed. Therefore, asking respondents to recall their last purchased menu item can be matched to the firm’s database of regional menu prices, allowing the base alternative in the choice set to represent the real in-market price paid for the most recent real market purchase. Online experiments therefore provide a clear advantage on this point when compared to face-to-face or CATI data collection methods. (See table 2.)

The programming for this study monitored completion rates of categorized choice sets on an ongoing basis throughout the study. Available respondents, i.e those that were deemed suitable for this study from the ORU panel, were automatically assigned to the sampling stratum most needed, on a random basis. The large available sample meant the fulfillment process did not require increased prompting or increased incentives, thus avoiding sample fulfillment issues.

3. Churn and cannibalization

The study involved only the client’s customers, so we were forced to accept that the “no choice” option represented both “within menu” cannibalization and churn to another competitor. The regional nature of client’s business easily allows for churn, due to the close proximity of competitors. The proximity of competitors usually requires little effort for a respondent to move from one market participant to another, at times within reach of an easy walk.

TABLE 2
SAMPLE SEGMENTS FOR THE CASE STUDY

		Occasion Segment	
		Lunch	Dinner
Purchase Segment	Self	a	c
	Family	b	d

The “no choice” option was analyzed in terms of the combinations of hypothetical trade offs the respondent made throughout the experiment. By examining the utility of price against alternatives, we were able to understand the likelihood of churn based on either price or some other attribute, therefore offering insights into whether churn or cannibalization of the menu would occur.

Analysis

The analysis and modeling was conducted using McFadden’s (1974) Multinomial Logit Model (MNL) to derive the utilities for each menu item and its associated attributes and levels, such as price. Main effects, second order interactions and cross product interactions were estimated. The model also provided estimation of the utilities by demographic and meal occasion segment.

Figure 2 illustrates the utility thresholds for Family Meal Type 1, in order for the client to appreciate the maximum profit by retail menu price, independent of all other meal offers. As the analysis captured choice scenarios which were premised on a systematic and optimally efficient design, enabling clean estimations of attribute levels, we were able to plot all utilities via a second order polynomial function, i.e. a quadratic or parabolic curve. In cases where the experimental design is sub-optimal and the choice tasks are unrealistic or visually burdensome,

the orders of polynomial curves can increase along with the complexity of utility curves, thus making utility representations harder for the client to understand. In our case, however, we were able to achieve very clean and well-behaved estimates as reflected in figure 2. This meant the client was able to be presented with more intuitive curvatures that were easy to understand.

The revenue curve illustrates the maximum counter price that can be charged for Family Meal item 1 before revenue diminishes. Note that either side of \$4.60, the revenue is diminishing, thereby denoting \$4.60 as the optimal price for the meal.

The forecasts were recalibrated to actual market shares, so the changes to any menu item in the simulator reflected realistic movements in demand. Figures 3 to 6 depict the simulator anchored in real market share fluctuations, based on the changes the client would make when simulating both price and profit scenarios.

The DSS simulator provides adjustable bars for the end user to simulate varying price scenarios. The “Base” calculation is the difference between the base price for the item and the scenario price. (See figure 3.)

The nature of the dining occasion and diner simulation allows the end user to simulate market share based on

**FIGURE 2
PRICE AND REVENUE MAXIMUM**

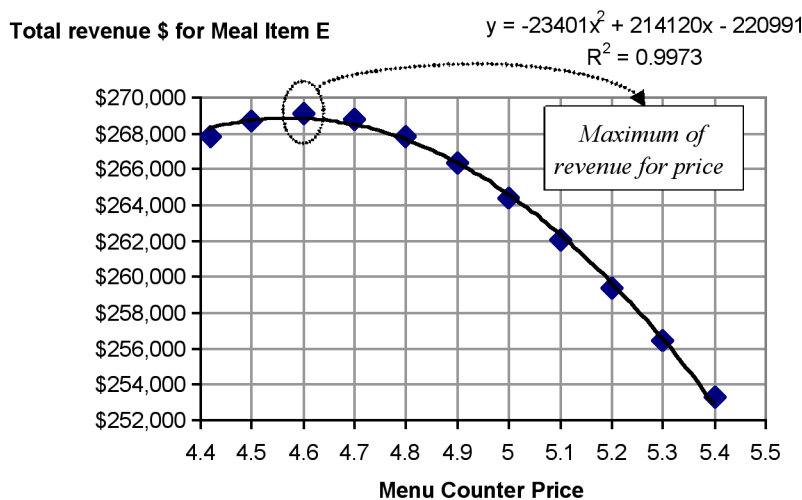


FIGURE 3
DSS SCENARIO SIMULATORS – ADJUSTING THE MENU PRICE

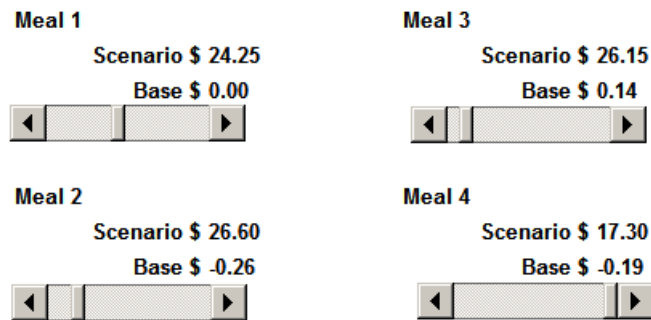


FIGURE 4
DSS OCCASION SIMULATORS – ADJUSTING DEMOGRAPHICS

Client Visit Status Client Profile

Last Month Visit	Gender
On a trip	Age group
Purchased At	

FIGURE 5
DSS MARKET SHARE STATISTICS

Market Share Simulation	Scenario	Current	Change
Meal 1	8.09%	8.09%	0.00%
Meal 2	33.02%	33.02%	0.00%
Meal 3	22.43%	22.43%	0.00%
Meal 4	21.06%	21.06%	0.00%
Will not visit	15.39%	15.39%	0.00%

restaurant client status visit and restaurant client profile. This provides the client the opportunity to model the impact of price via the visit frequency, whether the visit was a result of being on a trip or not, and the location of purchase. (See figure 4.)

As the end user models hypothetical scenarios via the DSS, the fluctuation of market share statistics enables the end user to understand the impact on compensatory adjustments in the market. The end user is therefore able to simulate price changes and immediately appreciate

the impact to market share. (See figure 5.)

As some end users respond to graphics more easily than numbers, a graphical representation of market share in the DSS enables these users to gain a two-dimensional appreciation of shifts in market share. Another reason for providing this visual facility in the DSS is to enable the depiction of market share fluctuations to the wider members of an organization who may not have the opportunity to familiarize themselves with the more technical workings of the DSS. (See figure 6.)

FIGURE 6
DSS MARKET SHARE STATISTICS GRAPHS

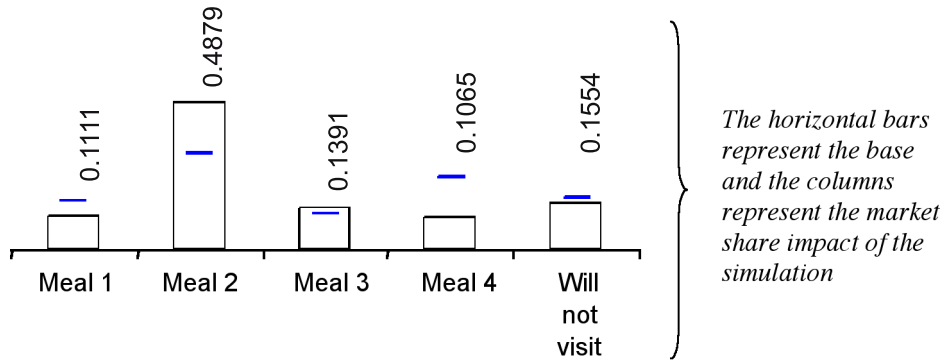


TABLE 3
COMPARISON OF DEMOGRAPHIC TO CART-TYPE WEIGHTING

Have Private Health Insurance	AMR	AMR+1	AMR+2-4	AMR+5-7	AMR+>7	Total	Population	Abs Diff
Unweighted	52,86	49,54	42,24	38,99	36,96	45,47	51,00	5,53
Demographic Weigh	65,44	62,26	54,25	51,33	48,11	58,35	51,00	7,35
Cart Weight	56,95	55,84	47,41	45,00	40,19	50,82	51,00	0,18

Weighting the data to market share

Recognizing that differences exist between people who are online and offline, our adopted weighting scheme takes account of this. As online panel members can belong to more than one panel, differences in panel composition also mean clear differences in attitudes, behaviors and demographics between respondents that belong to differing numbers of online panels (Fine, Menictas, and Casdas, 2006). In some instances, online panel members were found to belong to up to 10+ panels at the same time. We therefore identified a need to develop a weighting process by multiple panel membership to remove the differences due to panel composition.

In order to remove these differences so the ORU Online Panel sample reflected the population, a non-parametric weighting scheme was developed (Fine, Wang, and Menictas, 2007) using Salford-Systems CART, a classification and regression tree algorithm. CART has the unique ability of modeling both *main effects and all higher order interactions*, therefore providing a solution beyond multivariate techniques require the estimation of interactions as specific predictors. A non-parametric

classification tree approach such as CART models *all effects* simultaneously, something that would be almost impossible to achieve in propensity modeling using a regression approach, due to confinements such as multi-collinearity. The CART weighting approach has been tested on other data sets (Fine, Wang, and Menictas, 2007), and to date has performed well in allowing a weighting solution to remove the impact of polytomous categorical variables such as *panel composition*.

The CART weighting scheme aligned the total panel sample back to the population to capture both online and offline representation, as can be seen using one example of private health insurance in table 3. The re-weighted data was used in the analysis, so the DSS was free of the impact of degree of respondent panel membership. (See table 3.)

The weighting process therefore brought the data back to a realistic market share. The modeling of the weighting variable extended beyond standard demographics by including attitudes and behaviors as well as demographics. In addition, we modeled five panel composition categories and accounted for main effects

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and *n*-way interactions simultaneously. This ensured the estimates in the analysis were free of both sampling and panel biases. Using one of the models estimated for our client, we demonstrate the impact of removing the differences due to the degree of respondent panel membership. Table 4 contains a comparison of model fit statistics for un-weighted data, standard demographic type weighted data, and Cart-type weighting, where the differences in model fit vary significantly as evidenced in McFadden’s R-square and log-likelihood statistics.

We note also that model estimates are significantly different between the models due to weighting type (see table 5).

We can see therefore that when we correct for panel differences and gain a better model fit, the coefficients are also affected and this impacts client reporting.

Quality and validity of output

Validity of output

As we have discussed, to ensure realism, the consumer’s last choice was incorporated in the choice experiment. As consumer memory is fraught with high variability in recall, respondents were simply asked to recall their most recent meal from the client’s retail outlets (note: the sample was screened to ensure only recent purchases were included). The last meal chosen was price matched to the client’s data base for the particular region’s price schedule, to optimize the likelihood that the last meal price was an accurate representation of what would have been paid by the respondent.

Therefore, when respondents were presented with pricing alternatives in the choice experiment, their last

**TABLE 4
COMPARISON OF MODEL FIT DUE TO CART-TYPE CORRECTION FOR PANEL DIFFERENCES**

Fit Statistics	Unweighted	Demographic weight	Cart weight
McFadden’s Pseudo R-square	0.1019	0.1251	0.1422
log-likelihood	-1,178	-1,212	-952
aic	2,444	2,512	1,991
bic	2,653	2,724	2,193

**TABLE 5
COMPARISON OF MODEL FIT DUE TO CART-TYPE CORRECTION FOR PANEL DIFFERENCES**

Attributes	Unweighted coefficient	Demographic weighted coefficient	Cart-type weighted coefficient
β0	-3.733 ***	-4.762	-4.429 **
β1	-0.258	-0.190	0.054
β2	-0.146	0.075	0.487
β3	1.773 ***	2.342 ***	1.792 **
β4	0.170	-0.220	-0.190
β5	0.047	0.116 *	0.033
β6	0.031	0.052 ***	0.071 ***
β7	-0.043	0.094	0.085
β8	-0.443 ***	-0.470 ***	-0.587 ***
β9	-0.079	-0.149 *	-0.199
β10	-0.239	-0.298 *	-0.450 **

legend: **p*<0.05; ***p*<0.01; ****p*<0.001

PART 2 / DATA QUALITY

meal purchase price was in all likelihood that which the respondent had indeed paid for, forming the basis upon which to compare hypothetical alternatives.

This quest for pricing realism was one way of attempting to reflect reality in the discrete choice experiment. When screening respondents, asking for the last meal purchase without asking for the price paid placed lower demands on memory. Secondly, by presenting respondents the most recent price paid for the last meal when undertaking the experiment, the likelihood of respondents making realistic choice in the discrete choice experiment was enhanced.

Outputs: the decision support system (DSS)

The DSS in figure 7 was based on multinomial logit modeling and built in MS Excel using MS Solver, which derived utility estimates from the client’s current customer base to predict profit optimization. The client was able to manipulate both the price and cost/unit in

order to gain an understanding of both revenue and profit impact.

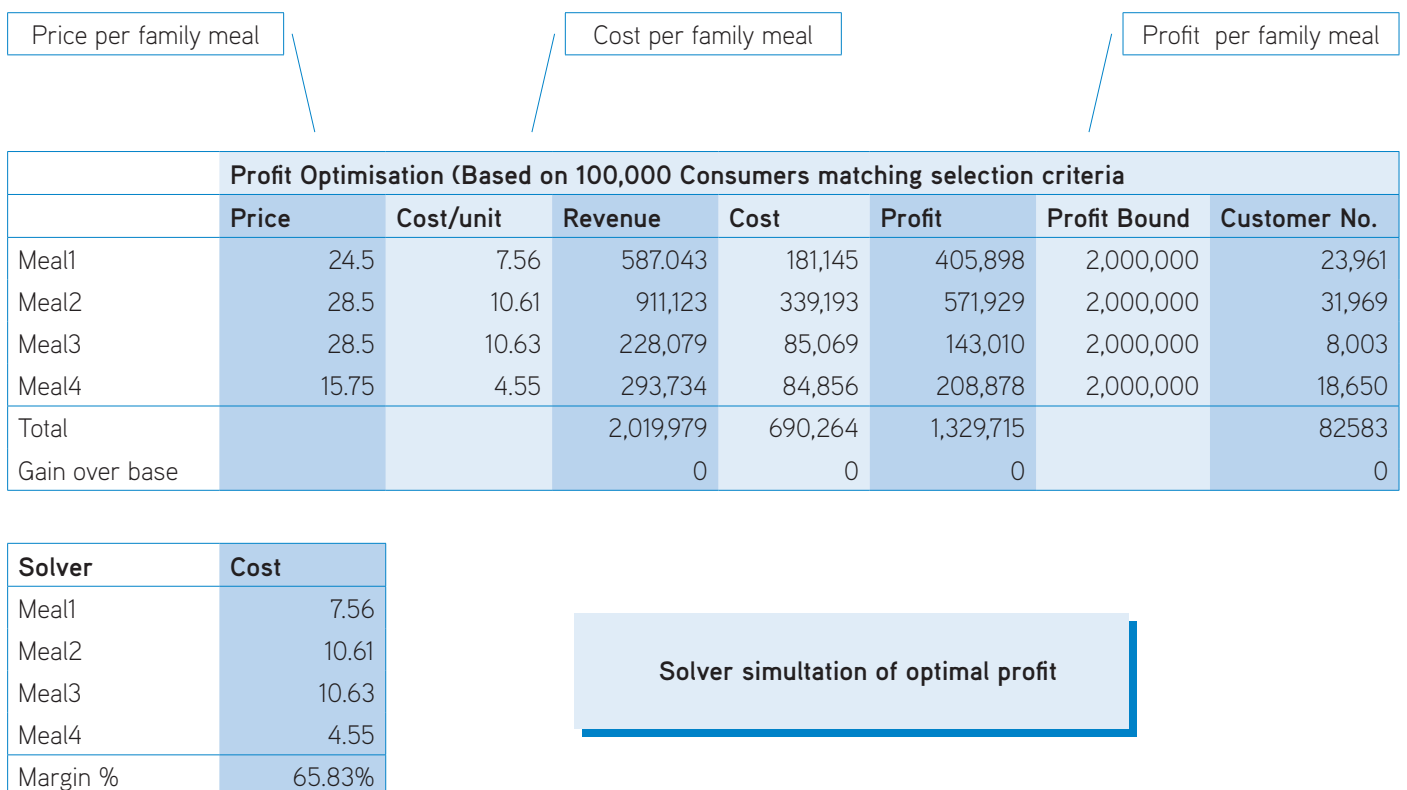
Churn and cannibalization was therefore understood in terms of the impact of revenue of one menu alternative to another.

The revenue profit simulator enables the end user to sacrifice profit in order to understand the impact on both customer numbers and market share. In order to perform the simulations, either the “Price per family meal” or the “Cost per family meal” would be adjusted to immediately depict the impact in profit and patronage.

What-if scenarios therefore provide the end user with the understanding of the impact of current versus hypothetical pricing, and menu planning simulations provide impact on market share due to change?

The revenue and profit simulator (figure 7) indicates menu combinations that suggest profit maximization

FIGURE 7
DETAILED DSS REVENUE AND PROFIT SIMULATION



across multiple menu items simultaneously. The use of real market meal prices matched to the respondent's most recent priced meal used as a choice benchmark provided the efficacy of the estimates.

The DSS also simulated "will not visit" options (figures 5 and 6), where the respondent would hypothetically churn (deflect their purchase) to the competition, thereby allowing the client to simulate both retention and customer churn. The client was thus able to understand the menu planning and pricing impact of simulated changes. Most importantly, the client was able to simulate increased customer spend based on meal sale price, i.e. the willingness of the client to reduce profits for an increase in demand in consumption. To this end, the simulation provided a conservative estimate of increasing demand, as the model was premised solely on current patrons, and did not estimate cannibalization from competitors who might not have been able to, or willing to, retaliate to the client's price reductions.

CONCLUSION

We have made an attempt to illustrate the benefits of using online panels in complex and demanding research such as discrete choice experiments and modeling. We believe that online panel research is quite unique in it being able to model complex combinations of existing and hypothesized scenarios in discrete choice tasks, and to classifying respondents into *a priori* choice task strata in real time. Online panel research can easily control for complex quota requirements regarding choice set balance, and to effortlessly present respondents visual presentations of intricate choice tasks that are universally comprehensible.

The ability of online research to present respondents revealed preference data in the form of their last purchase, and then to elicit their stated preferences in the form of choices to hypothetical scenarios, is a unique advantage when compared to existing experimental and data collection methods.

The key to being able to project preferences to the population, has been the modeling of attitudes,

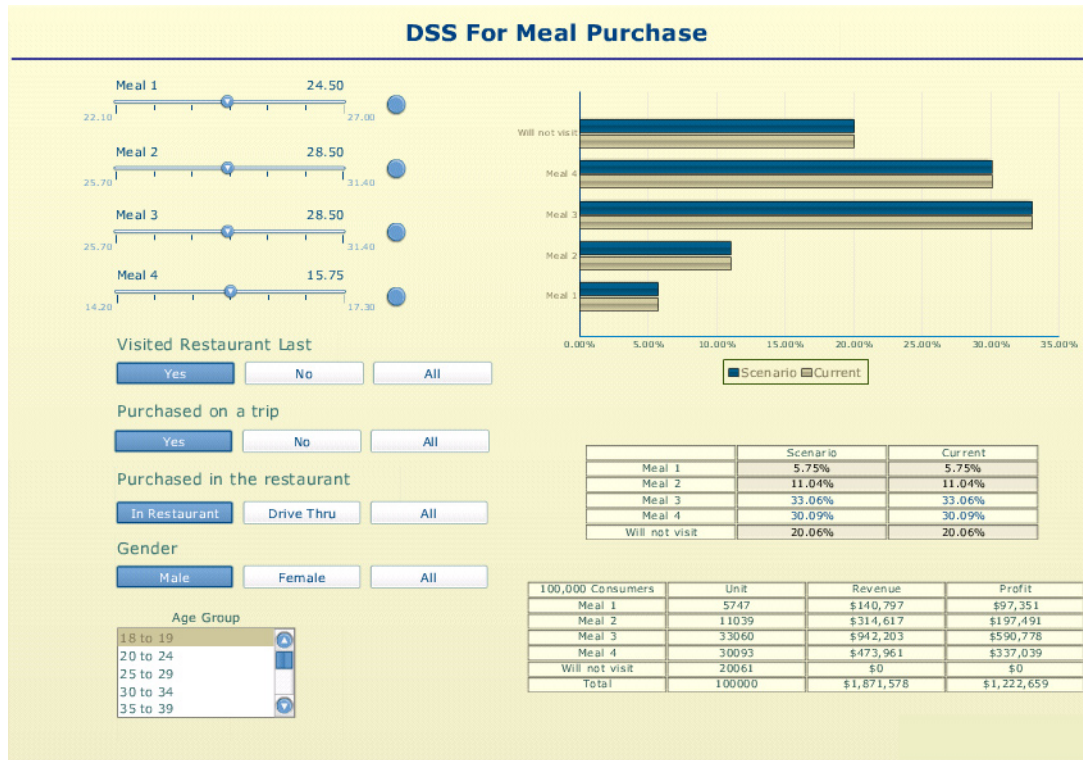
behaviors as well as demographics, by using a non-parametric procedure such as CART to account for main effects and *n*-way interactions.

As the discipline of experimental designs continues to evolve, in particular the recent work of Street and Burgess (2007), online research's ability to easily accommodate main effects and interactions in discrete choice experiments means that respondents are able to evaluate multidimensional and simultaneous options. This means that the researcher can get closer to the consumer decision process and understand modeling implications from a deeper level.

DSSs have been around for quite some time in marketing research in various form, however, we believe the aim of a DSS is to aid the manager to simulate consumer response in a way that is *intuitive* and *easy* to understand. To this end, we believe a quality DSS should aim to achieve three principal outcomes. First, a DSS should aim to avail the end user with what-if scenarios that are based on *real consumer behavior* data, such as the data used in this case study, to aid the realism of the decision making process. Second, the DSS should aim to provide *extended simulations*. An example would be a profit simulator, availing the manager the modeling of profit erosion to increase product demand, or attack a competitor. Third, a DSS should enable the user to easily *communicate* the simulations throughout the organization, thus extending the DSS to a wider audience. This increased organizational exposure can invite wider accountability for strategy formulation and can foster the exchange of information more widely within a company. As the DSS is a dynamic market model, it should be capable of being recalibrated with minimal outlay regarding future recalibration, thereby availing the client of cost savings in the future.

Our DSS has taken the output provided to the client to a level that now includes profit optimization and return on investment (ROI). This model identifies whether investing in price reduction will result in increased profits via sufficient additional sales, and "*within menu*" controlled cannibalization.

FIGURE 8
LATEST TECHNOLOGY DSS



We hope to have convinced the reader that as the nature of research is changing on a global level, online panels offer a sophisticated and more robust alternative to traditional data collection methods such as paper methods, CATI and CAPI.

In line with the advantages of online panel research, the ability to get closer to the consumer’s decision process is also a benefit we believe will be increasingly sought after and made possible by advanced quantitative methods.

We hope to have demonstrated the value of on-line panels when used for complex research with financially accountable simulations. To ensure the greatest efficacy, careful attention needs to be given to the rigor of online panel sample, research design, weighting and outputs.

Quality output for clients continue to be a challenge influenced by both the quality of online panels and the researchers that work with them. In line with the ARF online and quality initiative, we urge you to consider

all aspects of research, not only for the quality of the sample, but also the impact a researcher can have on the client decision making process and bottom line!

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