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Tournament-based conjoint modeling identifies effective message combinations.

If product positioning is the battle for the mind of the consumer, then product messaging provides the armamentarium at the disposal of the marketer in that struggle. The way in which a product is positioned is a critical stratagem for marketers confronted with the challenge of improving a product's standing in a competitive landscape. However, the actual execution of this positioning through powerful messages is what consumers ultimately see and is what drives them to decide whether to use a product.

While on the surface this appears to be a straightforward task, two issues complicate this process. First, there is often more than one message that marketers desire or need to communicate, and the question typically becomes which of these messages should be prioritized within the platform. The goal of most marketers is to develop a relatively concise message platform that addresses some combination of key themes that are consistent with the overriding positioning. For example a pharmaceutical marketer may want to tout a new medication's efficacy in communications directed toward physicians, but also touch on its safety, tolerability and high levels of formulary acceptance. Determining the composition of the platform and the order of a set of messages within that platform can be critical in maximizing the impact of the resulting mental positioning created in the mind of the consumer.

A second complicating issue is that the potential number of messages that can be generated for even the most straightforward

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product benefit can be very large. Therefore, it is not uncommon to be deciding between many different ways of conveying each message. Assuming that a minimum of five messages must be shown within an effective platform and that there are 10-20 possible wording variations per message, a marketer may face the challenge of narrowing 50-100 potential messages down to five. Consequently, identifying an appropriate methodology to select the "right number" and "best combination" of messages from a large universe of potential messages is critical.

Marketers frequently leverage primary research with likely end users to identify a combination of messages that resonate with the target audience and drive home critical points about a product. Some will use qualitative evaluations; others will rely on more statistically reliable quantitative approaches. However, attempting to cull down the number of messages, select a highly effective combination of messages and determine their most effective order in one modeling process can be daunting or even impossible.

TURF and Trade-Off Modeling

Current research methodologies often cannot adequately determine the best combination of messages, primarily because they are swamped by the sheer number of possible message combinations. Consider a case our research team recently encountered with a pharmaceutical company that was attempting to develop a five-message platform directed toward physicians. Altogether there was a pool of 60 potential messages from which these five messages would be selected. Therefore, the research needed to be designed to identify a group of five messages that maximized impact from a staggering 655 million possible five-message combinations. Even knowing that the client felt that the most effective messaging platform must contain one message from each of five conceptual buckets (e.g., efficacy, safety), there were still 125 or almost 250,000 possible message combinations.

One of the standard approaches for identifying highly effective message combinations is the total unduplicated reach and frequency (TURF) modeling approach. TURF models provide insight into the coverage of a bundle of messages. That is, they tell us the percentage of ndividuals within a particular population for which at least one message (in a group of messages) resonates. The TURF approach relies on respondent ratings of each message presented individually. In the pharmaceutical example, respondents were presented with each of the 60 messages one at a time, and they were then asked to indicate how compelling each message was using a one-to-10 scale.

TURF modeling itself is computationally straightforward in that, for each respondent, agroup of messages is identified that the individual finds compelling. Typically, these are messages for which the individual provided a "top box" response (e.g., giving it a rating of 8, 9 or 10 on a 1-to-10 scale). Once this is done, it is possible to calculate the total number of non-redundant respondents for which the messages are compelling. For example, assume that a two-message bundle contains messages that 35 percent and 22 percent of respondents respectively ranked as compelling. Yet of the 22 percent who found the second message to be compelling, half (11 percent) also found the first message to be compelling. Consequently, the coverage of this message bundle would be 46 percent—35 percent from the first message plus the non-redundant 11 percent of respondents from the second.

Executive Summary

How a product is positioned is a critical stratagem for marketers, so identifying an appropriate methodology to select the "right number" and "best combination" of messages is critical. Current research methodologies often cannot adequately determine the best combination of messages because they are swamped by the number of possible message combinations. We have developed a tournament-based conjoint modeling approach (TBCM) that yields highly effective message combinations to more accurately reflect respondent preferences.

While at a conceptual level this can be extremely useful, there are two cautionary issues with using a TURF approach to determine effective message combinations. The first issue is that it can obscure some of the subtleties in a data set. For example, TURF modeling typically requires dichotomizing the scale using a standard "top box" criterion (e.g., 8, 9 or 10 on a 1-to-10 scale).Turning a 10-point motivation scale into a variable with just two levels reduces the amount of information present in the data in two ways. For each individual, a one-to-10 rating is transformed into a binary variable: Either the message resonates with him or it doesn't. Also, if a message does resonate, the model does not distinguish between a higher rating (e.g., a 10) and a lower rating (e.g., an 8 or 9).

The second issue is that TURF modeling requires the use of individual message ratings to infer conclusions about message bundles. Because of this, it doesn't directly assess a message bundle's impact—whether a particular group of messages will compel one to act. Instead, its focus is on understanding the percentage of a population that will be exposed to a group of messages. The essential problem in solely relying on a TURF approach to prioritize messages is that rating messages individually means that they have a simple additive relationship with each other. This limits the ability of this approach to fully capture any synergies that arise from presenting multiple messages together. Furthermore, because it captures coverage and not impact, a five-message bundle may achieve maximum coverage (i.e., 94 percent of doctors find at least one message in the bundle compelling), but there may be other bundles with less coverage that are more powerful in motivating individuals to change their behaviors.

Conjoint and Discrete Choice Modeling

A distinctly different approach leverages conjoint modeling. With this approach, respondents are presented with a series of message bundles one at a time and are then asked to directly indicate how motivating each bundle is (i.e., it gauges the impact of messages rather than coverage as in TURF). This can be measured indicating how compelling or motivating the bundle is on a fixed scale, selecting a product from a larger set of products or allocating product choices across a competitive set. With this approach, respondents are presented with multiple message bundles. Each bundle contains a different combination of messages, the presence or absence of any particular message being systematically varied across presentations.

To make this approach work, the number of messages being tested usually necessitates the use of an experimental design. In the pharmaceutical example noted earlier, there are over 655 million different potential unique message combinations. In this case, we applied some commonly used constraints in this product category (i.e., each bundle would contain only one message from each message bucket, and the message order would remain constant). However, even with these constraints, there were still 125 or almost 250,000 possible combinations. This, of course, means that it is logistically impossible to present a respondent with all possible combinations of messages.

This issue is most often addressed by using an experimental design. Each respondent only sees a subset of all possible message bundles, and across all respondents the values for any combination can be imputed. In this way, an extremely large number of potential message combinations can be systematically whittled down to a more manageable set of combinations from the perspective of respondent burden (e.g., 64). With these numbers of total message combinations, each respondent is only required to respond to 8, 12 or 16 message combinations so that, across all respondents, the 64 message combinations are presented a sufficient number of times. The different message combinations are determined with an eye to being able to calculate utilities for each individual message which, in turn, permits impact to be determined for any message combination.

A conjoint approach is effective at capturing the differential impact of various message bundles. As opposed to the TURF approach, where a top box threshold is used, the conjoint approach uses all points of the scale. Consequently, it is able to capture more subtle differences between message bundles.

However, there is one critical downside to a conjoint approach: the need to consider multiple interaction terms. One of the advantages of using a conjoint approach instead of TURF is that it captures the effect of presenting multiple messages together—and modeling the interactions between them. In theory, conjoint models are capable of capturing these "synergies" between any conceivable pair of two messages. However, with most studies, the number of messages being assessed makes it impossible to do this. This is because one of the critical assumptions underlying conjoint modeling is that the attributes are independent of each other. Therefore, to actually capture the impact of a two-message combination means that any given pair of messages must be presented as part of a message bundle at least twice to the same respondent.

On the surface this seems relatively straightforward. However, when there are a large number of potential messages and an experimental design is leveraged, presenting each possible message combination twice increases the complexity of the design to the point where an unrealistically large number of scenarios must be completed by each respondent. Consequently, researchers typically do not build this criterion into the design and, because of this, are unable to capture the true impact of two-way message interactions.

Tournaments and Bundles

Of the two approaches (TURF vs. conjoint), conjoint modeling is the most effective for determining the impact of an actual bundle of messages. However, as noted earlier, when a large number of messages must be assessed, the feasibility of the approach is compromised. We have developed a tournament-based conjoint modeling approach (TBCM) that addresses this concern and consequently yields highly effective message combinations that more accurately reflect respondent preferences.

The TBCM approach leverages a message tournament followed by a conjoint task to provide a complete picture of the impact of any given message bundle. It addresses the conjoint modeling issue of having to test too many message combinations by having each respondent complete a "message tournament" immediately prior to completing the conjoint task. This prior task effectively restricts the number of messages that are presented to the same respondent in the subsequent conjoint task. (See Exhibit 1.) To do this, respondents are presented with different groups of messages and, for each group, are asked to identify the one or two most compelling messages. Winning messages from each group are then pitted against each other in the same manner, with the respondent selecting the most compelling message. This process is repeated until the five to six most compelling messages are identified. These messages are then fed forward into the subsequent conjoint task that the same respondent completes. This effectively sidesteps the pitfalls that can arise from having to test a very large number of messages.

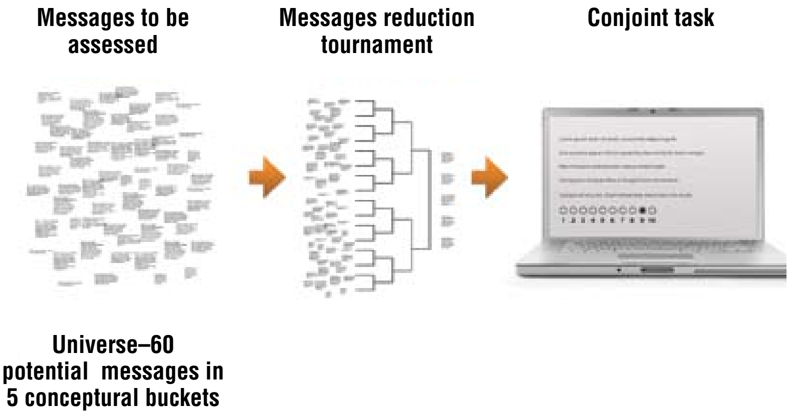
Given that the number of total messages is significantly reduced by the tournament, the message bundles can be systematically varied in the conjoint task in terms of their size (the number of messages) and their order (a particular message combination may be presented multiple times in a different order) in addition to their composition without increasing respondent burden to the point where data quality is compromised.

There are obviously other ways of reducing the number of messages in the conjoint task. However, one of the strengths of the TBCM approach is that the messages that are used in the conjoint task are customized to each respondent. Using a within-respondent tournament to cull down the number of messages effectively ensures that the messages presented in the conjoint tasks are those that the respondent finds most compelling.

To illustrate, consider the pharmaceutical example where a universe of 60 individual messages yields a total of almost 250,000 different possible combinations. Using the TBCM approach, it is possible to reduce the universe of messages from sixty to five and the total number of possible combinations from 250,000 to 120 potential five-message bundles. With 120 possible combinations, we were able to present respondents with a sufficient number of these combinations using a conjoint approach to address the concern raised earlier (presenting every possible message pair twice to each respondent) and consequently to make valid estimates of any combination of messages. When all was said and done, we were able to provide our pharmaceutical client with a group of highly effective three-, four- and five-message bundles, all of which were highly useful. In this way, our client was able to consider other priorities in addition to impact to determine the best messaging approach to incorporate into its communications directed toward physicians.

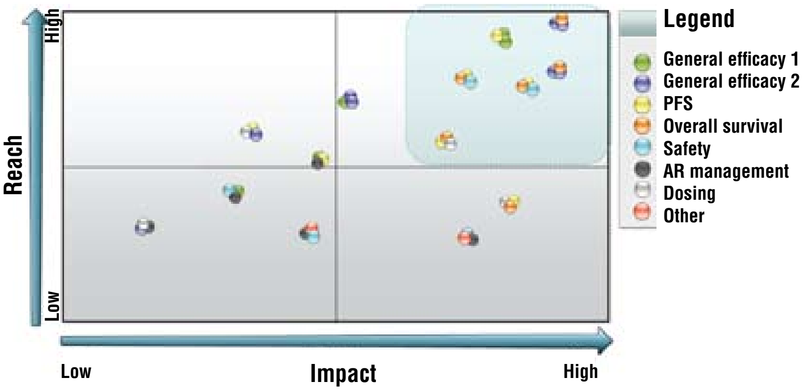
The one major methodological challenge involved with leveraging this approach is the ability to obtain sufficient data for all messages. Because each respondent assesses the impact of message bundles generated from a limited number of messages, it can be a challenge to ensure that there are enough observations for each message across all respondents to

Exhibit 1 Restricting messages



There is one critical downside to a conjoint approach: the need to consider multiple interaction terms.

Exhibit 2 Mapping message bundle impact



permit the accurate estimation of its impact within different bundles.

This is addressed in two ways. First, a sample size must be established that is large enough to ensure that most messages are included in the conjoint tasks for at least 10 respondents. While there is no precise algorithm for determining this, a sample size of 200 for each of two physician specialties proved to be sufficient from an analytic perspective for the pharmaceutical case described above.

However, a sufficiently large sample size does not completely address a second analytic barrier—that "not all messages are created equal." The messages that have relatively broad appeal will be significantly over-represented in the message bundle assessment and those that have an extremely limited appeal will be significantly under-represented. Consequently, even with a relatively large sample size, it can be a challenge to obtain a sufficient number of observations for messages with limited appeal. To address this, a second set of message bundles is presented to each respondent such that one message that was not selected from the tournament is incorporated into each bundle at random. This effectively ensures that even less compelling messages will be presented in the conjoint exercise a sufficient number of times.

There are a number of advantages to this approach. The most obvious is that it enables marketers to identify a highly effective bundle of messages from a large universe of potential messages and do so in a way that accurately captures the synergies between different message combinations. However, one of the less apparent benefits of this approach is that, when leveraged in conjunction with a TURF approach, it provides two different ways of assessing the effectiveness of a particular bundle of messages. The TURF modeling is based on responses to individual presentations of each message and provides an indication of the coverage of a message bundle. Conjoint modeling, on the other hand, is based on responses to the presentation of message bundles and provides an indication of the overall impact of groups of messages.

To capture this, we advocate mapping the coverage and impact of different message bundles on a 2 x 2 matrix. (See Exhibit 2.) This matrix provides a strong visual summary of message bundle impact. It can be used to differentiate those bundles that are strong on both dimensions and those high impact/moderate coverage bundles that can then be used in conjunction with other factors outside the research to identify a combination of messages that a marketing team will use moving forward.

Implications

There are several key implications for both marketers and market research professionals in leveraging the TBCM approach to message prioritization. The methodological advantages noted here add to the confidence that both marketers and researchers can have in the results. However, another primary benefit is that it ultimately makes the process of identifying a messaging platform less costly and time-consuming. Reducing a large universe of messages is sometimes addressed by preceding a quantitative phase that includes a conjoint task with a qualitative one. The objective of the qualitative phase is to cull out less effective messages and effectively reduce the overall universe of messages to be tested. While this sometimes achieves the end goal of a smaller universe of potential messages, it adds to the overall time and the cost of the research as this smaller universe of messages still needs to be fed forward into a quantitative study that will ultimately identify a highly effective message platform.

Additionally, qualitative research is usually effective at understanding why certain messages do and do not resonate and consequently can provide the impetus for new messages or prudent modifications to existing ones. However, it often does not yield a definitive reduced set of messages. This is mostly attributable to the inherent variability in preferences found in most populations. Given smaller qualitative sample sizes, it becomes more difficult to determine appropriate decision rules for culling out less appealing messages and ultimately coming up with a more manageable number. In contrast, the TBCM approach takes away the need for the prior qualitative step. The methodology effectively accomplishes what the initial qualitative phase does, but does so within the overall quantitative survey. Furthermore, the process of separating more appealing messages from those that are less appealing is done on a respondent-by-respondent basis. Consequently, the conjoint task is focused only on messages that are compelling and relevant to the individual, which ultimately yields higher quality data and more valid results. ●

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