

WhitePaper



Revealing Implicit Brand Drivers

Marco Vriens, Chief Research Officer, Ipsos MarketQuest

Alessandro Martins-Alves, Director, Ipsos Marketing, Brazil

Douwe Rademaker, CEO, Ipsos MarketQuest



Ipsos MarketQuest

Summary

Research has shown now that implicit perceptions can be very different from explicit perceptions and that both types can have an impact on behavior. This POV from Ipsos R&D reveals new insights:

1. Implicit brand attribute perceptions reveal very different brand drivers than explicit brand attribute perceptions.
2. Using both implicit and explicit brand attitudes leads to an extended set of insights as to how to drive preference for your brand. These new insights can be used to derive brand and shopper activation specific takeaways.

The neuroscience of brand attitudes and perceptions

There are several behavioral economics insights that show that humans don't always optimize utility when making decisions and that they are likely to rely in part or even fully on heuristics (i.e., more simple decision strategies). First, behavioral economists refer to a System 1 and System 2, where System 1 is more automatic, autonomous, unconscious, faster, intuitive and driven by more emotional factors, whereas System 2 is more conscious, controlled and slower. Second, there is the notion of bounded rationality, claiming that people don't have the time, resources and interest in weighing all available alternatives and therefore they are likely to engage in decision strategies that are referred to as "satisficing." Basically they will evaluate alternatives on attributes that they can relatively easily get information on and then pick the one that is good enough. So consumers won't go out of their way to search for information about alternatives but rather rely as much as possible on what is easily available: be it pulling information from memory, or choosing between what is (easily) available in store (distribution), or what draws most attention in the stores (attention, activation).

The implication of this is that consumers are more likely to use brand associations they have fast access to rather than relying on those associations that require conscious mental energy to access. This led to an innovation in measuring attitudes referred to as implicit attitudes in contrast to the traditional measurement of attitudes, referred to as explicit attitudes. Implicit attitudes are referred to as attitudes that influence our behavior without awareness. Explicit attitudes are those for which one has had the time to think about before providing the response. The fact that there is time to think or time has been taken prior to giving a response means the association is harder to retrieve, and hence can be affected by biases, such as the social desirability bias, Halo effect, etc. Implicit measures are said to avoid such biases and tap into more strongly processed associations. According to Implicit Attitude Theory the brain holds an intricate network of associations that are the result of experiences, perceptions and repeated exposure to messages (i.e., advertising) advocating certain perceptions. The richer these structures are and the more a certain belief is connected to such experiences and exposures the faster we can respond when asked if we associate a certain belief with say a specific brand (Moses, 2015). So, the time to respond becomes the tool to classify a respondent's association as either implicit or explicit.

Ipsos, in collaboration with Neurohm (our partner firm that specializes in implicit attitude measurement), uses response time to distinguish between what is considered a fast response versus what would be considered a slow or neutral response in terms of speed. A fast response is referred to as an implicit response.



Why are implicit attitudes and perceptions important?

There are two reasons why implicit attitudes are important:

1. They are important because the implicit responses on brand attributes can look very different from explicit responses to brand attributes and hence can result in different recommendations.
2. They are important because they reveal different drivers. This leads to significantly different recommendations.

For reason one, let's consider the following two questions:

- (A) Do you associate Apple with innovative?
- (B) Do you associate Citibank with trust?

Chances are more consumers would say yes to question (A) more and faster than to question (B). Say, a consumer survey shows that 65% put Apple in the top-2 box on a 5-point scale. For Citibank this number is 71%. However, if we take into account speed, and only count the top-2 box response if the response was given fast then we might find only 56% to give Apple a top-2 box rating and 33% to give Citibank a top-2 box rating. It is clear from these results that Apple is more strongly associated with "Innovative" than Citibank is with "Trust" if we consider the implicit responses.

It is also clear that the explicit responses suggest the opposite. So, as a diagnostic tool in brand research and advertising research this is incredibly useful because we can easily see on what attributes the brand is truly strongly positioned. Does this matter though? What do implicit attitudes toward a brand really tell us and how would it affect how we think about a brand and potentially how to manage it?

For reason two: Implicit attitudes and perceptions have been found to be predictors (drivers) of actual behavior. Studies have looked at the role and predictive power of implicit attitudes in the context of consumer behavior and showed that implicit attitudes can improve the prediction of behavior over and above the use of explicit attitudes only

In all of the published studies the implicit attitude was captured in only one variable and the explicit variable was captured in one variable. This limits the usefulness of these findings with respect to standard approaches in brand research where firms typically consider a fairly large number of potential brand associations (we see ranges from 10 all the way up to a 100 plus attributes). In the following pages, we outline how to use multiple implicit perceptions in brand driver models.

Implicit data in multivariate brand analytics

To get brand insights researchers usually rely on a variety of analytic tools such as driver models, segmentation analyses and brand mapping (e.g., multidimensional scaling). If implicit attitudes results look different than explicit attitude ratings then it is very likely that brand driver models, segmentation and mapping analyses give very different insights too.

This is important for two reasons. First, it may very well be that the relative importance of implicit and explicit differs across types of attributes. Second, implicit scores may be less susceptible to response style effects. In that case implicit scores may be less likely to be correlated. If this is the case, the number of significant drivers will go up because the inflated error variance that is the result of multicollinearity is reduced. So the implicit data should result in a higher number of significant drivers. This would have a significant impact on the actionability of the results.

Case Study: Smartphones

To show how brand drivers can be different when we base them on implicit perceptions we analyzed brand data for smartphones. We ran two types of models: (1) We modeled brand recommendation as a function of implicit perceptions and explicit associations, and (2) We modeled “How close do you feel to this brand.” By having one model with implicit perceptions and one model with explicit perceptions we can compare how the relative impact of implicit versus explicit varies by attribute. We can also test whether indeed the implicit model will yield more significant drivers.

Our data set

Ipsos has survey data on smartphones that was collected in 2013 (N=340) and covered three brands (Apple, Samsung and Blackberry). Respondents evaluated one brand each. We ask how close they feel to a brand (this is a standard question in Ipsos’ Brand Value Creator approach). In addition, respondents were asked if they agreed with the same set of brand statements, which were, namely:

This is a brand that:

- | | |
|---------------------------|-----------------------------|
| (1) I would recommend | (7) Is popular |
| (2) Is for me | (8) Is socially responsible |
| (3) Is different | (9) Is trustworthy |
| (4) Is high quality | (10) Sets the lead |
| (5) Is highly recommended | (11) Stirs my emotions |
| (6) Is on its way up | (12) Meets my needs |

Applying reaction time to develop implicit measures

For each brand statement above a 5-point agreement scale was used ranging from “Totally not agree with” to “Totally agree with.” In addition we have for each of these brand associations a parallel variable that indicates how fast the response was given. This response variable is pre-processed by Neurohm in their Implicit Reaction Time approach. In this approach respondents are calibrated based on their Internet speed connection, respondent characteristics, syllable and word length, basic motor skills, and cognitive responses to some training questions to develop benchmarks for speed of response. This speed of response variable is recoded into three values: fast, neutral, and slow. This recoding is done by Neurohm and is based on benchmarks they have developed. The raw (explicit variables) are now used to create a parallel set of implicit variables. For each brand association, if the respondent gave it a top-2 box rating and they gave it fast (as indicated by the speed variable) then it stays a top-2 box score. If the rating was given neutral or slow a top-2 box rating (1) will be recoded in to a bottom box score (0). A bottom box score remains a bottom box score regardless whether it was given fast, neutral or slow. Using this recoding, we in essence are giving more weight to the implicit responses.

The impact of IRT on brand driver results

In the first set of models we used brand attribute associations to predict an “I would recommend” association. We have two versions of this model: using the implicit associations and using the explicit associations. Each is estimated at the brand level. Note that for these models either all variables are implicit or they are all explicit. In the second set we estimated models to predict an attitudinal component of brand equity (“How close do you feel to this brand?”), measured only as explicit attitude. In this case we have one model where the independent variables are explicit and we have one model where the independent variables are explicit, though the dependent variable was explicit.

This first set of models is estimated at the brand level, i.e., two different binary logit models were estimated for each brand: one using the explicit data and one using implicit data. The results are shown in Exhibit 1.

Exhibit 1: Explicit versus Implicit Model for Smart Phones

Attributes	Apple		Samsung		Blackberry	
	Explicit	Implicit	Explicit	Implicit	Explicit	Implicit
For me	2.16	2.27	1.85	1.54	NS	1.75
Is different	NS	1.00	NS	1.07	1.25	1.25
Is high quality	1.23	0.70	NS	0.59	NS	2.30
Is highly recommended	NS	0.68	0.91	NS	1.73	1.03
Is on its way up	NS	NS	NS	0.95	NS	NS
Is popular	NS	NS	NS	0.65	NS	1.43
Social responsible	NS	1.84	NS	NS	NS	1.12
Is trustworthy	0.90	NS	NS	1.20	1.89	1.86
Sets the lead	NS	1.27	NS	1.26	2.04	2.12
Stirs my emotions	0.87	NS	NS	NS	NS	NS
Meet my needs	1.50	1.99	1.07	1.50	1.48	NS
# of significant drivers	5	7	3	8	5	8

Orange means only implicit or explicit is significant, NS means non-significant

Grey means both implicit and explicit are significant

We observe two interesting differences between the set of implicit and explicit models. First we observe that the drivers between the explicit model and the implicit models are very different across brands. Second, we observe that under the implicit data we have more significant drivers than under the explicit data. In some cases these differences are very large.

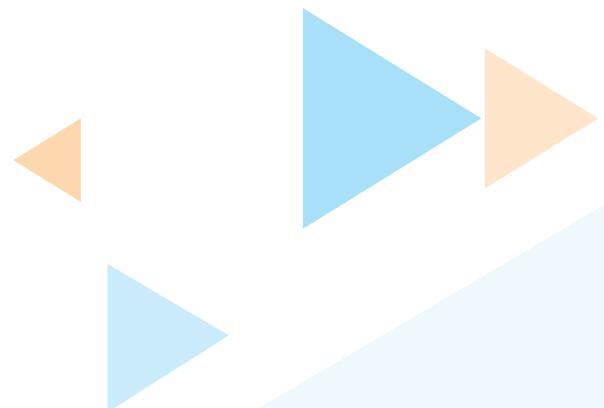
The second set of driver models is trying to predict ratings on the “brand closeness” variable (this variable is only available in an explicit format), a component of Ipsos Brand Value Creator. These models are estimated at the category level (as is typically done in such studies). Again we have two models: one with a set of explicit independent variables and one with a set of implicit independent variables. The results are shown in Exhibit 2.

Exhibit 2: Explicit model versus Implicit Models for Closeness

Attributes	Smart Phones	
	Explicit	Implicit
For me	1.55	0.95
I would recommend	NS	0.62
Is different	NS	NS
Is high quality	NS	0.47
Is highly recommended	NS	0.34
Is on its way up	0.68	0.61
Is popular	NS	0.38
Social responsible	NS	0.42
Is trustworthy	NS	NS
Sets the lead	NS	NS
Stirs my emotions	0.66	0.74
Meet my needs	NS	0.64
Number of sign. drivers	3	9

Orange means only implicit or explicit is significant, NS means non-significant
 Grey means both implicit and explicit are significant

The results are very similar to the results of our first set of driver models. We see clear differences between implicit and explicit drivers, and again we note that the implicit model systematically identifies more drivers (such as “high quality,” “is recommended,” etc.). The results of this category level model are interesting because in this case our implicit measures were able to predict an explicit measure (closeness). This is consistent with what other researchers have found when they investigated alternatives to reduce multicollinearity. We also ran these types of models on several other categories (including credit cards) and found similar results.



Conclusions

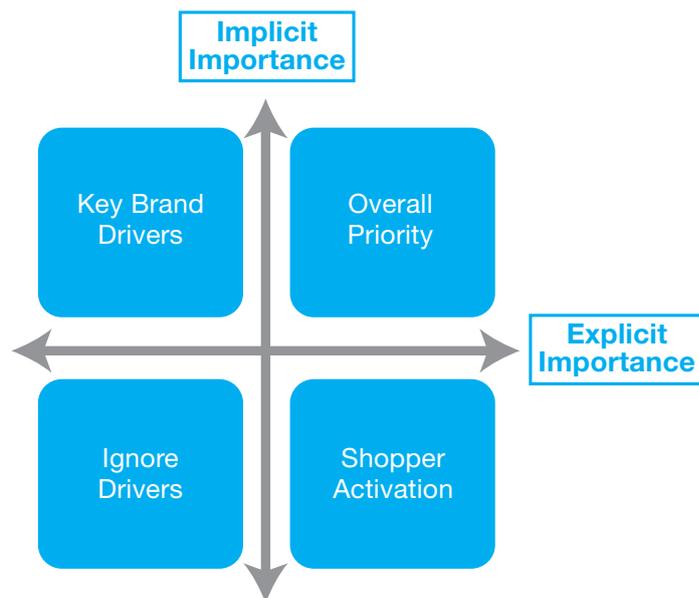
Our research shows that the implicit (System 1) drivers are very different from the explicit (System 2) drivers. Second, our research found that using implicit data results, on average, in a lot more significant drivers. This might be the result of implicit data being less susceptible to response style effects (we found some evidence for that). To our knowledge this is the first study that has looked at this in a multivariate context. We also compared implicit and explicit data in terms of how they would give different insights when used in segmentation and brand mapping analyses. The results were very different and we believe better when done with implicit data. These results are available upon request. Others have found the implicit attitudes improve the prediction over and above what we can predict with explicit. We think it is important for brand directors to look at and understand both types of attitudes.

Implicit measurement as done by Ipsos extends the usual brand driver insights by revealing a set of hidden drivers that are not accessible using the standard way of doing things. It can be used in most brand research and is an approach we are currently embedding in Ipsos Censydiam research, whereby we study the human motivations for brand preferences, as well as in our new Brand Dip research where we do a mobile enabled version of Censydiam.

Managerial implications

Our results have several implications for brand and category management. A brand manager needs to prioritize strengthening attributes where poor implicit scores reveal a weakness that might have looked like a strength when only looking at explicit results. A brand manager also needs to pay attention to both implicit and explicit drivers. Consider the matrix in Exhibit 3. The top in Exhibit 3 shows drivers that are implicit to be important – so these drivers should be part of any core branding strategies. The lower right quadrant has drivers that only play a role if consumers have time to think so any “reminders” via packaging or shopper activation can help consumers take these into account while making their decision.

Exhibit 3: Explicit versus Implicit Drivers



Brand managers must also keep in mind that explicit attributes are only going to be used or used more if they can be easily accessed: that is, if they are being put front and center in the store shopper activation environment. Promotions, coupons, and in-store displays should leverage explicit attributes. They don't need to evoke the implicit drivers as these are already accessed and used by consumers. For example, Apple may want their online ads to incorporate an emotional element that stirs prospective consumers, as that attribute plays a role but not in the implicit response. Or, think about a scenario where Crest wants to create an in-store promotion campaign to get consumers to switch from Colgate to Crest. For the Crest brand director it would be very useful to know the explicit drivers of Crest preference and hence use these as design principles in their promotions. The brand building efforts should primarily focus on: (1) maintaining their position on the implicit drivers, and (2) strengthening the positioning on those explicit drivers: those that the brand would like to become implicit. For shopper activation the brand should primarily leverage the explicit. The question is: should the manager focus specifically on the explicit attributes that are not also implicit attributes or should the managers focus on the congruent attributes (i.e., those attributes that are both implicit and explicit). We don't know the answer to this question yet but leveraging both types of attributes through branding and shopper activation will give better brand results.

References

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GAME CHANGERS

