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Modeling the implicit brand: capturing the hidden drivers

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Modeling the implicit brand: capturing the hidden drivers

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Abstract

Purpose – This paper aims to investigate modeling implicit attitudes as potential drivers of overall brand attitudes and stated behavior and investigate how the results are expected to be different from brand driver models that are based on explicit attitudes.

Design/methodology/approach – Data are collected via online surveys in five countries across 15 categories with sample sizes for each category/country combination in the range of about $N = 1{,}000$.

Findings – Implicit attitudes result in a higher number of significant effects than their explicit counterparts when used to explain behavioral intentions, brand closeness and brand usage in a multivariate situation with potential 12 brand attitude drivers. The authors also find fewer counter-intuitive effects in the implicit models. The results are consistent across 5 countries and across 15 categories (including CPG products, services and durable goods). They also show that implicit attitudes are less susceptible to response style effects (e.g. social desirability bias).

Research limitations/implications – The findings have implications for brand building and shopper activation. Further research should look into the impact of using implicit data on finding different brand segmentation and brand mapping results.

Practical implications – The findings have implications for brand building and shopper activation.

Originality/value – This paper contributes to the fast-growing field of implicit attitudes. The paper confirms and generalizes previous findings. This is the first paper to the authors' knowledge that has investigated the impact of implicit attitudes on overall brand attitudes and stated behavior in a multivariate context.

Keywords Neuroscience, Brand evaluation, Regression analysis, Information processing, Brand performance, Dual processing, Implicit attitudes

Paper type Research paper

1. Introduction

Behavioral economics and neuro science have credibly shown that human decisions do not always optimize utility, and they are likely to rely in part or even fully on heuristics (Gigerenzer and Gaissmaier, 2011). This has led to the description of a Systems 1 and 2 (Stanovich and West, 2000; Kahneman, 2003; Evans and Stanovich, 2013), where System 1 is more automatic, autonomous, faster, more intuitive way of making decisions and choices (Weinberg and Gottwald, 1982; Bargh, 2002). System 1 is supposedly also driven more by emotional factors (Phelps, 2004; Phelps and LeDoux, 2005; Heath, 2009; Smith and Nosek, 2011). System 2 is more conscious, controlled, and it is slower and assumed to be more rational. System 1 decision making is largely unconscious to the consumer. Emotional processing and response is very fast and does not seem to require conscious effort (Mast and Zaltman, 2006), may not require attention and can be more important in creating brand favorability than rational cognitive reasons (Heath *et al.*, 2006). Bargh (2002) shows that consumers' behavior can be unconsciously influenced by using priming effects.

These psychological findings and theories have led to an innovation in measuring attitudes referred to as implicit attitude measurement in contrast to the traditional measurement of attitudes, referred to as explicit attitudes (Greenwald and Banaji, 1995). Implicit attitudes are referred to as attitudes that influence our behavior without awareness (Stanley *et al.*, 2008). Implicit attitude and brand theory (Krishnan, 1996) states that the brain holds an intricate network of associations that are the result of experience, perceptions and repeated exposure to messages (i.e. advertising) advancing 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 (Friese *et al.*, 2006; Moses, 2015). The implicit association test (IAT) is the most used methodological approach to measure implicit attitudes (Greenwald *et al.*, 2003; Cunningham *et al.*, 2001). This approach has been used in most academic research but does not lend itself well for practical commercial brand research. Hence, in this study, we deploy a different methodology. Explicit attitudes are those for which one has had the time to think about before providing the response (Spence, 2005). Explicit attitudes are usually

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captured in semantic differentials, standard rating scales or simple yes/no association statements.

There have been studies in marketing that have investigated the relative impact of explicit and implicit attitudes on consumer preferences and behavior. However, to our knowledge in all these previous studies a single variable was used to measure the explicit attitude toward a brand or a product, and a single variable was use to represent the implicit attitude toward a brand or a product. As such these findings are hard to generalize to practical brand studies. Standard approaches in brand research typically consider many potential brand associations which can range from 10 all the way up to a 100 plus attributes. In this paper, we aim to make the following contributions. First, we expand on the literature by investigating how implicit attitudes can be modeled in typical multivariate situations that are used in brand, advertising and shopper research (in our case 12 potential brand associations). Second, we study whether brand driver models based on implicit responses yield different results as compared to driver models based on explicit brand association scores. Specifically, we investigate whether implicit based driver models differ from explicit based models in terms of fit as indicated by in-sample and hold-out sample fit, the number of significant attributes, the number of counter-intuitive effects in the brand driver models and the average relative coefficient (across the statistically significant attributes). We investigate these four questions using three different types of dependent brand variables: recommendation, brand closeness and brand usage. Our study covers 5 countries and 15 categories.

2. Literature review and hypotheses

The dual-processing theory (e.g. differentiating between Systems 1 and 2) states that behavior is driven "by reflective and impulsive processes" (Friese *et al.*, 2009). Implicit attitudes have sometimes been found to be better predictors of actual behavior than explicit attitudes (Greenwald *et al.*, 2009). Friese *et al.* (2007) found that an implicit attitude improved the prediction of future voting behavior over and above explicit attitudes. Nock *et al.* (2010) show that the use of implicit attitudes significantly improved the prediction of whether patients who were seeking psychological treatment for depression were going to commit suicide. In the context of socially sensitive topics, implicit attitudes have indeed proven to be better predictors of behavior. To generalize that to marketing situations is not as obvious. Only a handful of studies have looked at the role and predictive power of implicit attitudes in the context of consumer behavior. In Karpinski and Hilton's (2001) study, implicit attitudes were not able to predict the choice between an apple and candy. Ayres *et al.* (2012) did not find any incremental predictive accuracy of implicit attitudes over explicit attitudes in terms of predicting the choice between a healthy snack and an unhealthy snack. Maison *et al.* (2004) captured both implicit and explicit attitudes in three studies pertaining to preferences for yoghurt, fast food restaurants and soft drinks. Using multiple regression analysis, they showed that implicit attitudes (measured by the IAT) can improve the prediction of behavior over and above the use of explicit attitudes only. In all three studies, the regression weight for the implicit attitude was smaller than the regression weight for the explicit variables. We note that both the implicit and explicit attitudes were captured by a single variable, so we have no insights into their effects in a multivariate context. Also, the sample sizes in this study were very small (<50) for two of the three studies, and a $N = 103$ for their third study. Perugini (2005) in two studies pertaining to smoking behavior compared three models:

1 an additive model where both implicit and explicit are significant drivers;
2 a dissociative model where explicit attitude predicts a deliberate choice and implicit predicts a spontaneous choice; and
3 a multiplicative model that contains an interaction term between implicit and explicit.

He found some support for the multiplicative model (Study 1) and some support for the dissociative model (Study 2). Friese *et al.* (2006) studied preferences for ten CPG products and tested both branded and generic products. They found that 85 per cent implicitly preferred the branded versions. However, the explicit responses revealed that only 33 per cent preferred the branded products. Their results indicated that consumers choose mostly based on their explicit attitudes except if they had to make these choices under time pressure. We will comment on these results further in the discussion section. Vantomme *et al.* (2006) tried to predict which consumers had bought fair-trade products. A logistic regression model was estimated with as dependent variable whether they bought fair trade products and with as independent variables one explicit attitude and one implicit attitude. Both variables yielded significant regression coefficients, and in this study, the regression weight for explicit was larger than the regression weight for implicit. Richetin *et al.* (2007a) show that explicit attitudes predicted both incidental and deliberate behavior, whereas the implicit attitude only predicted the incidental behavior. Also, the impact of implicit can be moderated by a person's decision-making style. Richetin *et al.* (2007b) tested whether implicit attitudes would improve a prediction of whether or not consumers would prefer a fruit over a snack (binary dependent variable). They estimated a logistic regression model, and in their model building, they first included the implicit attitude and then entered the explicit attitude. Both variables remained in the model as significant predictors of the food choice. Though the fit of the model was low (17 per cent explained variance): the explicit variable received a coefficient of 0.51, and the implicit variable achieved a coefficient of 0.36. Friese *et al.* (2012) found that both implicit and explicit attitudes predicted voting behavior. A binary model with only one implicit attitude correctly classified voters' choices 89.5 per cent of the cases. Even when an explicit attitude was entered both effects remained statistically significant. As stand-alone predictors, the explicit attitude was a stronger predictor.

The empirical evidence suggests that both implicit and explicit attitudes toward a brand will have an effect on brand preference and usage metrics and we expect the explicit based models to have a somewhat higher (predictive) fit:

H1. Models based on implicit attitudes will have somewhat lower fit and predictive accuracy than models based on explicit attitudes.

Implicit responses differ from explicit responses in the speed in which a consumer can give the response. If a consumer is not immediately very confident about a certain brand statement it will take more time to respond to whether they associate that brand-attribute with the brand. More time needed to think prior to giving a response means the association is harder to retrieve. It also means there is more time and opportunity for response biases (social desirability bias, Halo effect, etc.) to enter in the response. Response style effects in survey data inflate the inter-correlation between brand association ratings. Implicit attitude ratings should be less vulnerable to this problem. Inter-correlations between independent variables in a regression analysis can cause (multi-)collinearity which makes it harder to identify significant effects because the confidence intervals around the regression weights go up (Yoo *et al.*, 2014). If you remove or reduce (multi-)collinearity the number of statistically significant coefficients will go up. It is also possible that the number of counter-intuitive effects will go down. We define a counter-intuitive effect as a finding that goes against common sense: e.g. if a brand is perceived to be of higher quality, we would expect it be recommended more often.

There is another reason why we would expect a higher number of statistically significant effects in implicit brand driver models. There is the notion of bounded rationality, a term coined by Simon (1957). He claimed that people do not 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" (Gabaix *et al.*, 2006). Basically, they will evaluate alternatives on attributes that they can relatively easily get information on and then pick the one alternative that is good enough based on this easily available information. In other words, consumers will not go out of their way to search for information about alternatives but rather rely on what is easily available: be it by pulling information from memory, or choosing between what is (easily) available in the store (distribution), or what draws most attention in the stores (e.g. visibility, activation). Bounded rationality theory states that consumers are more likely to use associations that they have fast access to rather than relying on those associations that require conscious mental energy to access. Because their decision strategy is focused on satisficing, they will simplify their decision task resulting likely in a small set of attributes, i.e. 6 (plus/minus 2) or less attributes because short-memory cannot contain more information (Miller, 1956; Saaty and Ozdemir, 2003). The implicit attributes are not bound by such limitation, as they are likely to reside in the long-term memory. The neural basis of implicit attitudes has been studied (Stanley *et al.*, 2008; and Phelps and LeDoux, 2005). Brain research, using functional magnetic resonance imaging, has linked implicit attitudes, but not explicit attitudes, to the Amygdala region of the brain, a region involved in emotion, memory and automatic responses (Phelps, 2004; Paz *et al.*, 2006). Automatic responses are only feasible if the information resides in long-term memory. Consumers likely use more implicit attitudes than explicit attitudes because the former can be more easily accessed. Specifically, we expect:

H2. Brand driver models based on implicit attitude measures will have a higher number of statistically significant brand drivers relative to brand driver models that are based on explicit brand attitude measures.

The expected higher inter-correlations of the explicit brand attributes scores causes the variance around the estimated regression coefficients to go up (increased multi-collinearity). This means that coefficients that are small or close to zero can easily be either positive or negative. If we expect these coefficients to be positive, then multi-collinearity will cause some of these coefficients to become negative. Hence, an increased number of counter-intuitive effects. All attributes in this study were positive attributes, i.e. higher scores should be more appealing then lower scores. Any negative coefficients could be considered counter-intuitive. Thus, we expect:

H3. Implicit brand driver models will have a lower number of counter-intuitive effects than explicit brand driver models.

We expect that the average regression coefficient in the implicit brand driver models may be higher than the average regression coefficient in explicit models. However, in all previous studies the explicit coefficient was always higher than the implicit coefficient (Karpinski and Hilton, 2001; Maison *et al.*, 2004; VanTomme *et al.*, 2006; Richetin *et al.*, 2007b; Ayres *et al.*, 2012). Given that the previous studies were based on models with one explanatory variable, we expect in our multivariate case to see higher average values for implicit coefficients relative to the explicit coefficient.

H4. The average regression coefficient in an implicit driver model will be somewhat higher than the average regression weight in an explicit driver model.

3. Methodology

We have survey data collected in 2013 by Ipsos. In all, 15 product categories were covered across 5 countries. For each category, we covered three brands. See Table I for an overview of the categories, brands, countries and sample sizes.

Previous research on implicit measures within a marketing context has mainly focused on food products (e.g. choosing between a healthy versus unhealthy snack, fruit versus snack, yoghurt, fast food and soft drinks). Such choices can be expected to be significantly influenced by unconscious, more emotional processes as for some consumers those choices may carry a stigma that they may not consciously want to admit to. For marketing, we need to know whether the implicit attitude results presented in the literature can be generalized. We chose a set of different categories to assess whether implicit attitudes play a role in situations that might not be so evidently influenced by emotional factors (e.g. laundry detergent, facial tissue), that the impact of implicit is really systemic and not limited to certain categories and that it is even relevant for categories where we might expect very deliberate (explicit) choices (e.g. credit cards). The literature has found that even when explicit information is present, implicit attitudes can still play a role (Shapiro and Krishnan, 2001).

For each category and for each brand, we ask how close they feel to a brand (this is a standard brand question that has been

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Table I Overview of categories, brands, sample sizes and countries

		Sample sizes				
Categories	**Brands**	**UK**	**US**	**Russia**	**Brazil**	**China**
Chocolate	Cadbury Dairy Milk Bars, Malte	1038				
Social media	Brands: Facebook, Twitter, LinkedIn	1056				
Department stores	Mark & Spencer, Amazon, John Lewis	1035				
Cars	Kia, Toyota, Volkswagen	1013				
Airlines	Delta, United, American		1005			
Credit cards	Visa, Mastercard, American Express		999			
Smartphones	Apple, Samsung, Blackberry		1020			
Fashion retail	Zara, H&M, Mango			990		
Carbonated Softdrinks	Coca-Cola, Pepsi, Sprite			1011		
Toothpaste	Colgate, Blend-a-met, Lacalut			1002		
Beer	Brahma, Antartica, Budweiser				996	
TV	Samsung, LG, Sony				1332	
Female deodorant	Nivea, Dove, Garnier bi-o				993	
Facial tissue	Vinda, Mind act upon mind, Tempo					999
Sportswear	Nike, Adidas, Li-Ning					1032

shown to be very highly correlated with a brand's market share) (Hofmeyr *et al.*, 2008). We also ask about usage. Stated brand usage is a proxy for behavior and as such an important aspect of evaluating the role of implicit attitudes. The usage variable and the way it was coded for analysis varied by category. For example, for beer, we used whether the brand was bought in the past four weeks, for televisions whether they own a specific brand, etc. The various usage definitions were derived from what is typically used by the brands in their commercial studies. Table II shows the usage definitions that were used in our analyses.

In addition, respondents were asked if they agreed with the same set of brand statements; e.g. this is a brand that I would recommend, for me, is different, high quality, is highly recommended, is on its way up, is popular, is socially responsible, is trustworthy, sets the lead, stirs my emotions and meet my needs. The list of brand attributes used in the study were created in collaboration with some of the included

Table II Overview of usage variable

Category	**Definition usage**
Chocolate	Have used brand within the last four weeks (Y/N)
Social media	Use daily (Y/N)
Department stores	Shopped less than two weeks ago (Y/N)
Cars	Own it or have owned (Y/N)
Airlines	Flew with airline less than a year ago (Y/N)
Credit cards	Used less than seven days ago (Y/N)
Smartphones	Currently own it (Y/N)
Retail fashion	Shopped there less than three months ago
Soft drinks	Bought last seven days
Toothpaste	Bought less than three months ago
Beer	Bought in past four weeks (Y/N)
TV	Currently own it (Y/N)
Female deodorant	Used in the last seven days (Y/N)
Facial tissue	Bought within past four weeks (Y/N)
Sportswear	Bought within past four weeks (Y/N)

brands in the study. For each perception, a five-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, a firm that specializes in implicit attitude measurement. In this approach, respondents are calibrated on their internet speed connection, respondent characteristics, syllable and word length, basic motor skills and cognitive responses to some training questions. This continuous variable is recoded in to three values: fast, neutral and slow. This recoding is done by Neurohm and is based on benchmarks they have developed. To prepare this data for analysis that allows us to compare explicit to implicit results, we recoded the brand associations in to binary variables (1 if top-2 box, 0 otherwise). 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 for the implicit counter-part. 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 are giving more weight to the implicit responses. The recoding process was because we needed to create a parallel set of variables: one for explicit and one for implicit, that have the same number of categories.

We develop three types of models, all at the category level:

First, we model brand recommendation as a function of implicit and explicit associations. By having one model with implicit predictors and one model with explicit predictions, 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. For these two models, all variables are either all implicit or all explicit.

Second, emotional connections are key in driving brand favorability as suggested by Heath *et al.* (2006). Thus, we want to understand if and how implicit drivers affect a positive brand attitude as measured by an attitudinal brand equity measure (Hofmeyr *et al.*, 2008). This can give additional insights as to how to change a brand's favorability and equity. Brand closeness was only captured in an explicit fashion, so in both models the dependent variable is explicit but the independent variables can be either explicit or implicit.

Third, we model brand usage as a function of either implicit attitudes or explicit attitudes. The nature of the dependent variables is shown in Table II.

All models are binary logit models. These models are robust and can capture non-linear relationships which have been found to be relevant in identifying the effects of attitudes (Van Doorn *et al.*, 2007). We evaluated the models by looking at the (1) the in-sample fit of the models (based on 80 per cent) of the sample and the out-of-sample or predictive fit (based on a 20 per cent hold out sample), (2) the number of statistically significant variables (at the $p < 0.10$ level), (3) the number of statistically significant counter-intuitive effects and (4) by looking at the average size of the coefficients.

4. Findings

The in-sample and out-of-sample fit results of the implicit and explicit brand driver models are shown in Table III.

First, we see that the fit, both in-sample and out-of-sample, is good to very good. The results confirm *H1*. The differences are small though but the explicit models do result in a somewhat better fit.

Next, we look at the results with respect to the number of statistically significant variables (with intuitively the correct sign) and the number of counter intuitive effects. The driver modeling results are summarized in Tables IV and V.

The results show that the implicit models always contain substantially more statistically significant coefficients. This confirms our *H2*. Even with a stated behavioral variable we again see a higher number of statistically significant drivers for the implicit models relative to the explicit models. Table IV (bottom row) also shows that implicit models have substantially fewer counter-intuitive effects (Tables VI–VIII contain the detailed brand driver model results). These results strongly confirm *H3*.

Multi-collinearity did not seem to be a large problem in our data. The implicit scores are less correlated; its correlation varies from 0.1 to 0.3, whereas the explicit scores correlation varies from 0.4 to 0.7. Recall that we had two possible causes for the larger number of significant effects to happen: a statistical cause and the theory of bounded rationality would also predict this. We expect both factors to have been at play here given the dramatic and consistent difference in the number statistical significant effects.

Lastly in Table IX, we show the average coefficients for the implicit and the explicit models across the categories and across the different dependent variables.

As Table IX shows for "I would recommend", the average coefficient is clearly higher under the implicit models but this is reversed under the closeness and usage models. So, the evidence here does not support *H4* but is somewhat consistent with previous empirical findings.

5. Discussion

In this paper, we set out to investigate the implications of implicit attribute responses for brand insights. Various behavioral economics theories state that it is very likely that consumer's choices will be driven, at least partially by "System 1". To obtain insight into what attributes are evoked we compared the results of driver models that are based on explicit and implicit drivers.

Previous findings with respect to the fit or "explained variance" have found implicit models to explain less variance and/or have a lower fit. Our results confirm and generalize these findings (*H1*). Our results also show that the implicit (System 1) drivers are different from the explicit (System 2)

Table III In-sample and out-of-sample predictive fit of explicit and implicit models

	Recommend				Closeness				Usage			
	Sample (80%)		Sample (20%)		Sample (80%)		Sample (20%)		Sample (80%)		Sample (20%)	
Categories	Explicit	Implicit	Explicit	Implicit	Explicit	Implicit	Explicit	Implicit	Explicit	Implicit	Explicit	Implicit
Chocolate (%)	90.0	85.0	85.0	82.6	79.2	76.1	71.0	68.6	77.5	77.0	67.6	67.1
Social media (%)	89.8	86.1	87.6	81.0	84.5	84.8	85.2	81.4	82.2	75.8	77.1	67.6
Department stores (%)	91.2	86.8	85.5	83.6	78.3	76.4	85.0	74.4	74.8	72.9	73.9	72.0
Cars (%)	88.0	84.6	91.6	82.8	85.2	86.4	80.3	83.7	80.2	81.5	79.8	79.3
Airlines (%)	88.3	84.8	82.6	76.1	83.0	82.1	73.1	79.6	71.6	71.5	68.2	65.2
Credit cards (%)	88.6	84.6	87.6	87.1	79.9	78.1	77.1	76.1	71.8	74.2	69.7	71.6
Smartphones (%)	90.2	86.2	89.2	88.7	79.3	78.6	73.5	75.0	77.2	79.3	74.5	72.1
Fashion (%)	91.0	85.9	88.4	82.8	78.5	78.4	71.2	78.3	79.0	78.5	71.2	69.2
Carbs (%)	91.9	86.8	88.1	82.6	77.2	75.7	71.1	68.7	73.1	76.0	71.1	73.1
Toothpaste (%)	89.0	85.3	89.6	86.6	75.8	73.5	71.6	74.1	70.0	69.2	73.6	69.2
Beer (%)	89.2	85.3	91.9	85.4	77.7	80.2	79.8	78.3	77.6	79.6	80.3	78.3
TV (%)	91.7	89.7	92.9	88.4	68.2	66.6	71.5	69.7	61.4	63.7	57.7	65.2
Female deodorant (%)	90.4	86.3	87.4	83.3	71.9	75.3	73.2	71.2	69.8	73.1	68.2	73.2
Facial tissue (%)	86.6	83.6	88.1	83.6	69.0	66.2	67.2	75.6	70.8	70.7	74.1	75.1
Sportswear (%)	86.3	83.9	86.0	83.1	72.6	71.0	65.2	60.9	77.2	77.6	83.6	84.5
Average across categories	0.895	0.856	0.881	0.838	0.774	0.766	0.744	0.744	0.743	0.747	0.727	0.722

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Table IV Differences in number of significant attributes by category across the models

	I would recommend		Closeness		Usage	
Brand attributes	**Explicit**	**Implicit**	**Explicit**	**Implicit**	**Explicit**	**Implicit**
Chocolate	6	8	4	9	6	8
Social media	7	10	5	7	8	7
Department stores	6	10	4	8	4	6
Cars	8	11	4	6	5	5
Airlines	6	10	7	9	6	6
Credit cards	6	10	8	8	4	8
Smartphones	7	10	3	9	4	7
Fashion	7	11	4	9	4	7
Carbs	7	11	5	8	2	7
Toothpaste	7	11	5	10	2	7
Beer	7	11	5	9	4	8
TV	9	10	7	8	4	5
Female deodorant	8	10	5	10	3	7
Facial tissue	9	10	6	8	2	8
Sportswear	9	10	5	10	3	5
Average number of significant coefficients	7.36	10.20	5.13	8.53	4.07	6.73
Number of counter intuitive coefficients	1	0	6	0	6	3

Table V Differences in number of significant attributes by attribute across models

	I would recommend		Closeness		Usage	
Brand attributes	**Explicit**	**Implicit**	**Explicit**	**Implicit**	**Explicit**	**Implicit**
For me	15	15	13	15	12	15
I would recommend			6	14	7	12
Is different	7	15	2	5	2	3
Is high quality	11	14	1	13	0	5
Is highly recommended	15	14	5	10	2	9
Is on its way up	5	11	5	10	1	3
Is popular	8	15	4	14	4	9
Is socially responsible	3	13	1	6	0	4
Is trustworthy	14	15	1	12	2	8
Sets the lead	8	14	10	8	8	9
Stirs my emotions	10	12	11	9	9	9
Understands my needs	12	15	12	12	7	10
Average	9.8	13.9	5.9	10.7	4.5	7.9

drivers and we find on average a lot more significant drivers in the implicit models (*H2*). Bounded rationality theory states that consumers tend to simplify their decision task resulting likely in a small set of attributes and likely use six (plus/minus 2) or less attributes because short-memory cannot contain more information (Miller, 1956). The implicit attributes are not bound by such limitation. Our findings are consistent with this as most explicit models indeed have six or less significant attributes (only 3 out of the 45 models have 9 significant attributes which is outside the range of 6 plus/minus 2). The implicit models show 22 out of the 45 to have more than 8 significant coefficients. We also showed that implicit data are less susceptible to response style effects. The presence of response style and response bias effects has been shown to complicate or even disable the identification of (brand) drivers (Büschken *et al.*, 2013). Implicit measurement can be an additional tool to avoid or reduce this problem. The presence of response style effects can complicate the identification of drivers and multi-collinearity can lead to counter-intuitive effects and to lower average effects. We do see a lower number of counter-intuitive effects in the implicit models (*H3*). The mixed results for *H4* with respect to the average coefficients warrants further study. Previous literature has always found the explicit driver to be larger. To some degree this makes intuitive sense as respondents can respond in a deliberate manner, i.e. be more explicit in their stated responses. Our results are consistent with this and with the previous univariate research except for the results using the recommendation variable as a dependent variable. The recommendation variable is also measured implicitly which could have caused the implicit variable to be more impactful for that dependent variable but not for the other two dependent variables.

To our knowledge, this is the first study that has looked at the effects of using implicit measurement in a multivariate driver modeling context and has found this result. The

Table VI Explicit versus implicit models for 'I would recommend'

	Chocolate		Social media		Department stores		Cars		Airlines		Credit cards		Smartphones		Fashion	
Brand attributes	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance
For me	2.11	...	2.40	...	2.28	...	1.68	...	1.88	...	1.81	...	1.80	...	1.06	...
	1.86	...	1.93	...	1.81	...	1.76	...	1.16	...	1.43	...	1.80	...	1.38	...
Is different	NS		NS		NS		NS		NS		NS		0.65	..	0.75	...
	0.81	..	0.57	..	0.37	...	0.83	...	0.83	..	0.87	..	1.06	...	0.91	...
Is high quality	0.62	..	1.02	...	NS		0.77	...	0.74	...	0.58	..	NS		NS	
	1.24	...	1.10	...	0.88	...	0.46	..	1.38	...	0.35	...	0.34	...	0.84	...
Is highly recommended	1.58	...	1.10	...	1.28	...	0.93	...	1.08	...	1.40	...	0.30	...	0.88	...
	1.81	...	1.39	...	1.07	...	1.57	...	1.08	...	1.57	...	0.73	...	1.45	...
Is on its way up	NS		0.43	.	0.58	.	0.53	..	NS		NS		NS		NS	
	NS		0.78	...	1.33	...	0.60	..	NS		0.55	.	0.74	...	0.48	.
Is popular	0.73	..	NS		0.81	...	0.51	.	NS		NS		NS		1.01	...
	0.92	...	0.92	...	0.92	...	0.78	...	1.12	...	0.88	...	0.71	...	0.73	...
Is socially responsible	NS		NS		NS		NS		NS		NS		NS		NS	
	NS		NS		0.90	...	0.52	.	0.73	..	0.93	...	0.74	..	1.22	...
Is trustworthy	NS		0.87	...	0.89	...	1.13	...	0.99	...	1.03	...	1.13	...	1.03	...
	1.14	...	1.06	...	1.04	...	1.07	...	1.07	...	1.34	...	1.16	...	1.18	...
Sets the lead	0.74	..	0.67	...	NS		0.55	..	0.74	..	NS		0.71	..	NS	
	0.73	.	0.75	..	NS		1.08	...	1.68	...	1.04	...	1.27	...	0.71	..
Stirs my emotions	NS		0.75	...	NS		0.87	...	NS		0.62	.	0.57	.	1.42	...
	NS		1.58	...	0.90	.	1.07	...	0.79	..	NS		NS		1.24	...
Understands my needs	0.79	..	NS		0.59	..	NS		0.61	..	1.08	...	1.27	...	0.97	...
	1.13	...	1.19	...	1.45	...	0.79	...	0.78	...	1.08	...	1.53	...	1.40	...
No. of significant drivers	6		7		6		8		6		6		7		7	
	8		10		10		11		10		10		10		11	11

(*continued*)

Table VI

Brand attributes	Carbs Explicit Implicit	Carbs significance significance	Toothpaste Explicit Implicit	Toothpaste significance significance	Beer Explicit Implicit	Beer significance significance	TV Explicit Implicit	TV significance significance	Female deodorant Explicit Implicit	Female deodorant significance significance	Facial Tissue Explicit Implicit	Facial Tissue significance significance	Sportswear Explicit Implicit	Sportswear significance significance
For me	2.06	...	1.52	...	1.52	...	1.13	...	1.34	...	0.62	..	0.75	...
	1.87	...	1.15	...	1.42	...	0.46	.	1.18	...	1.08	...	0.65	...
Is different	0.45	.	0.74	...	0.53	..	NS		0.45	.	0.55	..	NS	
	1.02	...	0.81	...	0.59	..	0.60	..	1.01	...	1.30	...	0.60	...
Is high quality	NS		0.93	...	0.61	..	1.02	...	1.46	...	0.63	..	0.59	..
	0.59	..	1.33	...	1.03	...	1.27	...	1.65	...	0.38	...	NS	
Is highly recommended	0.34	...	0.50	..	1.47	...	0.63	..	1.13	...	0.75	...	0.67	...
	1.17	...	1.38	...	0.95	...	0.89	...	1.28	...	NS		0.41	.
Is on its way up	NS		NS		NS		NS		−0.51	.	0.77	...	0.54	..
	0.83	...	0.45	.	0.37	...	NS		NS		0.42	.	0.67	...
Is popular	NS		NS		NS		0.63	..	0.45	.	0.72	...	0.43	.
	0.35	.	0.58	...	1.39	...	1.03	...	0.68	..	0.85	...	0.70	...
Is socially responsible	1.13	...	NS		NS		0.33	.	NS		NS		0.33	.
	1.73	...	0.99	...	0.85	..	0.76	...	0.89	...	0.63	...	0.54	..
Is trustworthy	1.91	...	1.03	...	0.88	...	1.46	...	0.60	..	0.34	...	0.72	...
	1.88	...	1.26	...	1.25	...	1.50	...	0.31	...	0.84	...	0.72	...
Sets the lead	NS		NS		0.53	.	0.72	...	NS		NS		0.46	.
	0.95	...	0.99	...	1.18	...	0.33	...	0.31	...	0.38	...	0.37	...
Stirs my emotions	1.04	...	0.57	..	NS		0.54	..	NS		0.46	.	0.44	.
	1.54	...	0.99	...	0.80	..	1.29	...	0.69	.	0.53	..	0.49	..
Understands my needs	0.54	.	1.05	...	0.69	..	0.88	...	1.15	...	0.52	..	NS	
	0.82	..	0.84	...	1.13	...	1.11	...	1.26	...	0.75	...	0.64	...
No. of significant drivers	7		7		7		9		8		9		9	
			11		11		10		10		10		10	

Table VII Explicit model versus implicit models for closeness

	Chocolate		Social Media		Department stores		Cars		Airlines		Credit Cards		Smartphones		Fashion	
Brand attributes	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance
For me	2.14	...	1.45	...	2.07	...	1.21	...	0.53	.	0.84	...	1.55	...	1.06	...
	0.35	...	0.86	...	0.60	...	0.53	..	0.44	..	0.72	...	0.35	...	0.87	...
I would recommend	NS		0.37	...	NS		NS		NS		0.87	...	NS		NS	
	0.73	...	0.61	...	0.83	...	0.71	...	0.41	..	0.68	...	0.62	...	0.48	...
Is different	NS		NS		NS		NS		NS		0.36	.	NS		NS	
	0.41	.	NS		NS		NS		0.67	...	NS		NS		NS	
Is high quality	NS		NS		NS		NS		NS		NS		NS		NS	
	0.53	...	0.60	...	NS		NS		0.47	..	0.56	...	0.47	..	0.65	...
Is highly recommended	NS		NS		NS		0.91	..	0.79	...	NS		NS		0.49	.
	0.54	...	0.68	...	0.30	.	NS		0.56	...	0.50	...	0.34	.	0.55	...
Is on its way up	0.71	...	NS		0.53	..	NS		NS		0.72	...	0.68	..	NS	
	0.67	...	NS		NS		0.57	..	0.44	..	0.37	.	0.61	...	0.34	.
Is popular	1.25	..	NS		NS		NS		0.59	..	NS		NS		0.91	.
	0.50	...	0.41	..	0.81	...	0.48	..	0.65	...	0.39	..	0.38	..	0.33	.
Is socially responsible	NS		NS		−0.34	.	NS		0.58	..	NS		NS		NS	
	NS		NS		NS		NS		NS		NS		0.42	..	NS	
Is trustworthy	NS		NS		NS		NS		NS		−0.65	..	NS		NS	
	0.28	.	NS		0.39	..	0.75	...	0.47	..	NS		NS		0.51	...
Sets the lead	NS		0.85	...	NS		0.96	...	0.64	...	0.44	..	NS		NS	
	NS		0.47	..	0.88	...	NS		NS		0.69	...	NS		0.45	..
Stirs my emotions	0.31	...	1.10	...	NS		1.37	...	0.70	...	0.42	..	0.66	...	NS	
	0.77	...	NS		0.45	.	0.90	...	NS		1.26	...	0.74	...	NS	
Understands my Needs	NS		0.69	..	1.13	...	NS		0.46	.	0.90	...	NS		0.65	..
	NS		0.61	...	0.72	...	NS		0.68	...	NS		0.64	...	0.44	..
Number of significant drivers	4		5		4		4		7		8		3		4	
	3		7		8		6		9		8		9		9	

(*continued*)

Table VII

	Carbs		Toothpaste		Beer		TV		Female deodorant		Facial tissue		Sportswear	
Brand attributes	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance
For me	1.23	...	1.56	...	1.58	...	NS		1.09	...	0.78	...	NS	
	0.86	...	0.79	...	0.30	...	0.58	...	0.49	...	0.69	...	0.42	...
I would recommend	NS		0.66	..	NS		0.55	..	0.79	..	NS		0.49	..
	0.60	...	0.76	...	0.82	...	0.32	..	0.59	...	NS		0.44	...
Is different	−0.50	..	NS		NS		NS		NS		NS		0.44	..
	NS		0.31	.	NS		NS		0.34	..	NS		0.31	..
Is high quality	NS		NS		NS		NS		NS		NS		0.48	..
	0.39	..	0.55	...	0.55	...	0.64	...	0.61	...	0.45	...	0.51	...
Is highly recommended	NS		NS		NS		0.83	...	0.69	.	NS		NS	
	NS		NS		0.38	..	0.64	...	NS		NS		0.46	...
Is on its way up	0.80	...	NS		NS		NS		NS		NS		NS	
	0.48	...	NS		0.75	...	NS		0.48	..	NS		0.32	..
Is popular	NS		NS		NS		−0.33	.	NS		0.84	...	NS	
	0.44	...	0.45	...	0.40	..	NS		0.30	.	0.71	...	0.32	..
Is socially responsible	NS		NS		−0.35	.	NS		NS		−0.38	.	NS	
	0.64	...	0.50	...	NS		0.23	.	0.31	.	0.41	...	NS	
Is trustworthy	NS		NS		NS		0.49	.	NS		NS		NS	
	0.47	...	0.28	.	0.44	..	0.52	...	0.60	...	0.39	...	0.50	...
Sets the lead	NS		0.41	.	0.83	...	0.36	..	0.65	...	0.64	...	0.58	...
	NS		0.69	...	NS		NS		0.30	.	0.33	..	0.50	...
Stirs my emotions	0.99	...	0.53	..	0.54	..	0.46	...	NS		0.48	..	NS	
	NS		0.71	...	0.78	...	0.33	..	NS		0.39	..	NS	
Understands my Needs	0.59	..	0.42	.	0.44	.	0.40	..	0.90	...	0.64	...	0.70	...
	0.35	.	0.4	..	0.66	...	0.37	...	0.59	...	0.47	...	0.29	.
Number of significant drivers	5		5		5		7		5		6		5	
	8		10		9		8		10		8		10	

Table VIII Explicit model versus implicit models for brand usage

	Chocolate		Social media		Department stores		Cars		Airlines		Credit Cards		Smartphones		Fashion	
Brand attributes	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance
for me	1.02	...	1.96	...	1.23	...	0.68	..	0.58	..	0.87	...	1.25	...	NS	
	0.66	...	1.21	...	0.46	...	0.70	...	0.37	.	0.61	...	0.76	...	0.39	..
I would recommend	0.69	..	0.80	...	NS		1.33	...	0.48	..	0.82	...	0.52	.	NS	
	0.45	...	0.53	...	0.69	...	0.75	...	NS		0.32	.	0.40	..	0.39	..
Is different	NS		−0.71	...	NS		NS		0.42	..	NS		NS		NS	
	NS		NS		NS		NS		0.36	.	−0.69	...	NS		NS	
Is high quality	NS		NS		NS		NS		NS		NS		NS		−0.52	.
	NS		0.46	..	NS		NS		NS		NS		NS		NS	
Is highly recommended	NS		NS		NS		0.55	.	NS		NS		NS		0.48	.
	0.30	.	0.43	..	NS		0.58	...	NS		0.50	...	0.37	..	0.34	.
Is on its way up	0.62	...	−0.83	...	NS		NS		NS		NS		NS		NS	
	0.53	..	NS		NS		NS		NS		NS		NS		0.41	..
Is popular	NS		1.22	...	NS		NS		0.37	.	NS		NS		NS	
	0.36	..	0.72	...	0.46	...	NS		0.50	...	NS		0.39	..	0.33	.
Is socially responsible	NS		−0.73	...	−0.73	...	NS		NS		NS		NS		NS	
	0.42	.	−0.64	...	−0.45	..	NS		NS		0.46	..	NS		NS	
is trustworthy	NS		NS		NS		NS		−0.44	.	NS		NS		NS	
	NS		NS		NS		0.61	...	−0.52	...	NS		NS		0.49	...
Sets the lead	0.40	.	0.75	...	NS		0.55	..	NS		0.34	.	0.50	..	NS	.
	0.60	...	NS		0.32	.	NS		0.46	..	0.44	..	0.44	..	NS	
Stirs my emotions	0.36	.	1.02	...	0.49	...	0.75	...	0.66	...	0.50	..	NS		NS	
	0.80	...	NS		NS		0.49	..	NS		1.01	...	0.46	..	NS	
Understands my needs	0.44	..	NS		0.82	...	NS		NS		NS		0.75	...	1.03	...
	NS		0.59	...	0.67	...	NS		0.54	...	0.31	.	0.88	...	0.36	..
Number of significant drivers	6		8		4		5		6		4		4		4	
	8		7		6		5		6		8		7		7	

(continued)

Table VIII

	Carbs		Toothpaste		Beer		TV		Female deodorant		Facial tissue		Sportswear	
Brand attributes	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance	Explicit Implicit	significance significance
for me	0.90	...	0.78	...	0.64	..	0.41	.	0.65	..	NS		NS	
	0.45	..	0.56	...	0.48	..	0.32	..	0.36	..	0.55	...	0.42	..
I would recommend	NS		NS		NS		0.61	..	NS		NS		NS	
	NS		0.42	...	0.63	...	0.48	...	0.48	...	0.38	..	NS	
Is different	NS		NS		NS		NS		NS		NS		0.44	.
	0.49	...	NS		NS		NS		0.46	...	NS		0.45	...
Is high quality	NS		NS		NS		NS		NS		NS		NS	
	0.52	...	0.38	..	0.34	.	NS		0.30	.	NS		NS	
Is highly recommended	NS		NS		NS		NS		NS		NS		NS	
	0.54	...	NS		NS		0.39	...	NS		0.34	..	NS	
Is on its way up	NS		NS		NS		NS		NS		NS		NS	
	NS		NS		NS		NS		NS		0.31	.	NS	
Is popular	NS		NS		0.72	...	NS		NS		0.63	..	NS	
	0.54	...	0.39	..	0.50	...	NS		NS		NS		NS	
Is socially responsible	NS		NS		NS		NS		NS		NS		NS	
	0.33	.	NS		NS		NS		NS		0.27	.	NS	
is trustworthy	NS		0.52	.	NS		0.42	.	NS		NS		NS	
	0.53	...	0.29	.	0.37	..	0.41	...	0.45	...	0.33	..	NS	
Sets the lead	NS		NS		0.76	...	NS		NS		0.50	..	0.64	..
	NS		0.52	...	0.56	...	NS		0.37	..	NS		0.41	..
Stirs my emotions	NS		NS		0.78	...	NS		0.35	.	NS		0.43	.
	NS		0.39	..	0.73	...	0.34	..	NS		0.36	..	0.57	...
Understands my needs	0.57	..	NS		NS		0.41	..	0.84	...	NS		NS	
	NS		NS		0.32	.	NS		0.56	...	0.47	...	0.32	.
Number of significant drivers	2		2		4		4		3		2		3	
	7		7		8		5		7		8		5	

Table IX Differences in average effect sizes

Models	Chocolate Explicit Implicit	Social media Explicit Implicit	Department stores Explicit Implicit	Cars Explicit Implicit	Airlines Explicit Implicit	Credit cards Explicit Implicit	Smartphones Explicit Implicit	Fashion Explicit Implicit	Carbs Explicit Implicit	Toothpaste Explicit Implicit	Beer Explicit Implicit	TV Explicit Implicit	Female deodorant Explicit Implicit	Facial tissue Explicit Implicit	Sportswear Explicit Implicit
Recommendation	1.10	1.03	1.07	0.88	1.01	1.09	1.00	1.02	1.16	0.91	0.90	0.82	0.76	0.66	0.55
	1.21	1.13	1.13	0.96	1.06	1.07	1.07	1.05	1.16	0.98	1.05	0.99	1.05	0.84	0.64
Closeness	1.25	1.01	0.85	1.11	0.61	0.49	0.96	0.78	0.62	0.72	0.61	0.39	0.82	0.50	0.54
	0.60	0.60	0.62	0.66	0.53	0.65	0.57	0.51	0.53	0.54	0.63	0.45	0.46	0.48	0.41
Usage	0.59	0.44	0.45	0.77	0.35	0.63	0.75	0.36	0.73	0.65	0.72	0.46	0.61	0.57	0.50
	0.52	0.47	0.36	0.62	0.29	0.37	0.53	0.39	0.48	0.42	0.49	0.39	0.43	0.38	0.43

implication is that implicit data reveal brand drivers that would otherwise remain hidden.

Our results have several implications for brand and category management. The implications for brand management are that managers need to pay attention to both implicit and explicit drivers and where needed need to prioritize strengthening attributes where poor implicit scores reveal a weakness that might have looked as a strength at first glance when only looking at explicit results. Friese *et al.* (2006) found the implicit consumer attitudes primarily played a role when they were under time pressure (or in situations where controlled behavior would be inhibited). 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 and understand both types of attitudes. Also, the finding of time pressure seems limiting but it is not. In the laboratory experiment respondents were told to take as much time as they needed for their explicit choice. This is rather unrealistic: Who shops like that? In many case, consumers are strapped for time, bombarded with too many choices and therefore likely will use System 1 (implicit). Second, explicit attributes are only going to be used or used more if they can be easily accessed, i.e. if they are being put front and center in the store shopper activation environment. Promotions, coupons, in-store displays should leverage the explicit. They do not need to evoke the implicit drivers, as these are already accessed and used by consumers. For example, if you are a credit card brand then you may want your online ads to incorporate an emotional element that stirs prospective consumers, as that attribute plays a role but not in the implicit response. We can also easily see that access to both implicit and explicit results can have dramatic effects on brand and shopper management. Say Colgate wants to create an in-store promotion campaign to get consumers to switch from Blend-a-met to Colgate. For the Colgate brand director, it would be very useful to know the explicit drivers of toothpaste preference and hence use those on which Colgate is strong or has an advantage as design principles in their promotions. The brand-building efforts should primarily focus on maintaining their position on the implicit drivers and strengthening the position on those explicit drivers: even more those that the brand would like to become implicit. For shopper activation, the brand should primarily leverage the explicit.

6. Conclusion

In sum, brand managers should consider and use the implicit approach when they fully want to understand the brand drivers.

There are several avenues for further research. First, more insight is needed in to the prevalence of implicit attitudes in driving actual brand choices, e.g. as being measured via market share data. In today's multi-media and attention-deficit world, we think the use of implicit attitudes might be quite prevalent and possibly more important than explicit attitudes. Plus, as mentioned, even when presented with explicit information, implicit attitudes may still have an impact on the consumer choices (Shapiro and Krishnan, 2001). Similarly, empirically explicit brand associations have been found to have an impact on brand consideration and the degree to which a brand comes to mind first to mind (Nedungadi, 1990). We need to understand if this also holds for implicit attitudes.

A second 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)? The literature refers to congruence if a stimulus (i.e. brand) is associated both implicitly and explicitly to an attribute. This is not always the case. For example, say consumers associate Colgate with freshness explicitly but not implicitly but they associate Colgate with cavity protection both implicitly and explicitly. The question is should they focus on freshness in the promotion/in-store activation or should they focus on cavity protection.

Third, we also expect differences in brand maps that are based on multidimensional scaling (MDS) and segmentation analyses. Perceptual maps as derived from MDS and correspondence analysis may look very different and better than the maps we derive from raw data. Implicit attitudes are a proxy for familiarity. Implicit attitudes are said to result from frequent exposures (i.e. advertisements, etc.) and experiences with the brand. See also how Alba and Hutchinson (1987) define familiarity, i.e. as the accumulation of product related experiences. Mano and Davis (1990) concluded that low familiarity resulted in less consistent MDS solutions and found that MDS goodness-of-fit measures increased with increased familiarity. MacKay and Zinnes (1986) argued that familiarity results in better input data. Likewise, clustering analyses for segmentation might work much better with implicit data. Some authors have argued there is no brand segmentation (Kennedy and Ehrenberg (2001). Because correlated attributes are or can be a problem in clustering the use of implicit measurement may find that brand segments indeed do exist.

Fourth, there is evidence that implicit attitudes are easy to form but may be difficult to change (Gregg *et al.*, 2006). If this is true, then this would have significant brand implications because implicit attitudes owned by the competition would not be good targets to go after. We leave these as topics for further research.

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