Customizing Persuasive Messages; the Value of Operative Measures

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Abstract

Purpose – This article examines whether estimates of psychological traits obtained using meta-judgmental measures (as commonly present in CRM database systems) or operative measures are most useful in predicting customer behavior.

Design / methodology / approach – Using an online experiment ($N = 283$) we collect meta-judgmental and operative measures of customers. Subsequently, we compare the out-of-sample prediction error of responses to persuasive messages.

Finding – The paper shows that operative measures—derived directly from measures of customer behavior—are more informative than meta-judgmental measures.

Practical implications – Using interactive media it is possible to actively elicit operative measures. This article shows that practitioners seeking to customize their marketing communication should focus on obtaining such psychographic observations.

Originality / value – While currently both meta-judgmental measures and operative measures are used for customization in interactive marketing, this article directly compares their utility for predicting future consumer behavior.

Keywords. Consumer behavior, Integrated Marketing Communication, Persuasive Strategies, Measurement, Customization.

Customizing Persuasive Messages; the Value of Operative Measures

An understanding of integrated marketing communication (IMC) is important for both academics and professionals (Peltier et al., 2003). IMC provides a holistic view on communication planning that recognizes the value of using a comprehensive plan integrating a variety of communication disciplines to provide clarity, consistency, and maximum impact (Peltier et al., 2003; Csikósová et al., 2014). IMC increased in popularity as a result of the evolution from mass-marketing advertising to targeted marketing messages (Berthon et al., 2000; Deighton and Kornfeld, 2009). IMC also conceptualizes the *customization* of communication: Peltier et al. (2003) present a model conceptualizing how database management and IMC jointly operate to create customized campaigns. Their model provides an overview of the relationships between consumer data, profiles, and the resulting communication plan.

However, the landscape in which IMC theory operates is changing. To start with, the opportunities to interact with consumers are increasing: marketing communication is moving more and more towards a genuine dialogue (Bezjian-Avery et al., 1998; Haeckel, 1998; Deighton and Kornfeld, 2009; Finne and Grönroos, 2009). Also, our abilities to collect data are evolving: we have moved from a general inability to measure consumer responses, to the use of electronic scanners, to a situation in which we can measure consumer responses to communication continuously (see e.g., Parvinen et al., 2014; Kaptein et al., 2013; Kaptein and Parvinen, 2015). This opportunity seems like a treasure throve for IMC scholars: we can now reap the fruits of interactive IMC (Jiang and Chia, 2010). We can customize marketing communication not just at the level of (relatively large) customer segments, but we can move towards true one-to-one marketing (Stone and Woodcock, 2014) . The ability to fully customize communication promises more effective, less wasteful, and more pleasant interactions (Moon and Lee, 2014).

To effectively customize communication it is essential to have access to the right sources of data. Consumer data, often stored in customer databases (e.g., CRM data), is needed to profile consumers and to estimate the effects messages will have on customers. In essence, the key to customization is the ability to predict, *for each individual consumer*, which marketing message is most effective (Ansari and Mela, 2003; Hauser et al., 2009). Thus, it is important to understand the utility of the different types of data that we have access to (e.g., demographic data, psychographic data, etc.). Despite an ever increasing access to data, effectively predicting customer responses and selecting marketing messages is still challenging. Although demonstrations of effective customization in interactive marketing do exist (see, e.g., Ansari and Mela, 2003; Arora et al., 2008; Hauser et al., 2009), truly living up to the promises of one-to-one marketing seems outside the reach of many firms. Arguably, as advocated by Webster Jr. (1998), our inability to live up to the promise of one-to-one marketing might be due to the absence of psychographic measures such as motivation, needs, and attitudes in many (CRM-) databases; a marketeer must understand the psychological factors that motivate the observed behaviors for effective customization.

In this paper we focus on the opportunity that arises within interactive (online-) marketing communication to obtain psychological trait scores of consumers not by using survey instruments, but rather by logging the behavioral responses of consumers to carefully crafted marketing messages. Subsequently, we demonstrate how these trait scores can be used for message customization and we show that the trait scores obtained using this method outperform traditional survey-based measures in terms of predicting future consumer behavior. The latter might seem obvious: most of us intuitively subscribe to the view that behavior of customers as witnessed (e.g.,) in a specific store is likely a better predictor of future behavior in that same store than any conceivable survey instrument administered in a different context. Our contributions are, however, to a) demonstrate in detail *how* we can quantify consumer behavior to obtain psychological trait scores, as opposed to consumer preferences, by carefully designing our marketing messages, b) *illustrate this approach for a specific trait*, namely *susceptibility to persuasive strategies*

(Kaptein and Eckles, 2012), that is highly valuable for marketing communication (Cialdini, 2001; Kaptein and Eckles, 2012), and c) demonstrating that our "gut-feeling" is correct: we demonstrate that actively elicited, direct, behavioral measures of trait scores not just outperform classical survey measures of the same traits, but do so by an order of magnitude.

Theoretical background

In this section we introduce our background theory and develop our hypothesis. We first embed our work in the literature on database management, IMC, and customization Peltier et al. (2003). Next, we explain the possible difficulties that arise when measuring psychological traits of consumers and focus specifically on the distinction made in the psychological literature between *operative* and *meta-judgmental* measures of consumer traits; a nomenclature we use throughout. Finally, we discuss persuasive strategies as a prime subject for message customization and develop our hypotheses.

Database management and IMC

A distinguishing feature of marketing customization is the interplay between database managent and the interactive IMC plan (Peltier et al., 2003). Database management concerns data collection, the subsequent curation of a database, and the process of segmenting or profiling customers based on the stored information. Next, an interactive IMC plan can be created for each segment to create customized campaigns, as illustrated in Figure 1.

Figure 1 highlights that multiple types of data can be of use in the customization process: a firm might have access to behavioral responses, demographics, and/or psychographic data. Each of these has its use, and likely the most effective customization can be attained by combining information from different sources (Kaptein and Parvinen, 2015). However, while behavioral responses that reveal consumer preferences are often easy to obtain, it is hard to obtain good psychographic measures despite their undisputed value in the customization process (Webster Jr., 1998; Hauser et al., 2009; Kaptein and Parvinen, 2015). This is especially true if we would like to obtain psychological trait scores, such as personality scores (Gosling et al., 2003), for all costumers included in a CRM database.

Psychographic measures are historically collected using surveys, which are often expensive or impractical to elicit from every customer. Because of this, and because of the ease by which behavioral responses can be collected by firms that operate largely online, database curation seems to have shifted its focus from collecting psychographic measures to curating behavioral and tracking data (Finne and Grönroos, 2009). However, we argue that interactive technologies provide us not merely with the opportunity to track customers but also with an alternative method to obtain measures of psychological traits: by deliberately selecting a marketing message and observing the behavioral response, we can make inferences about psychological traits of consumers without the use of surveys. To illustrate, consider a consumers *cognitive style*: survey instruments to measure cognitive style exist (Hayes, 1998), but recently Hauser et al. (2009) used the responses of customers to either textual or visually oriented messages to determine their cognitive style. Note that in this work, by presenting customers with strategically chosen messages, the researchers were able to actively learn about their psychological make-up. This opportunity of deriving, in interactive communication, psychological trait scores is tantalizing.

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Measuring consumer traits

Measuring psychological traits is hard, and a large measurement literature exists both in the marketing and in psychology (e.g., Geuens et al., 2009; Peter, 1979). There is a large body of work, under the heading of individual differences psychology (Dunton and Fazio, 1997; Furnham and Procter, 1989), that actively develops and evaluates measurement instruments for psychological traits. Examples include the measurement of personality (Gosling et al., 2003), emotional stability (Hills and Argyle, 2001), cognitive style (Huber, 1983), linguistic style (Pennebaker and King, 1999) and locus of control (Ajzen, 2002). Many of these traits have found their use in marketing, and also within marketing research measurement instruments are actively developed (see, e.g., Geuens et al., 2009).

The measurement of psychological traits is complicated by the "latent" nature of these traits; as opposed to (e.g.,) demographics, psychological traits can often not directly be observed and need to be deduced from a number of related measurements. A common approach is to generate a number of related survey items and use factor analysis (or the broader framework of structural equation modeling) to estimate consumer trait scores. In recent years scholars have begun to distinguish between formative and reflective measurement models (Cenfetelli and Bassellier, 2009). The scores on reflective survey items are said to be caused by the latent construct while the formative model operates in the opposite direction: the measured items directly cause the latent score (Coltman et al., 2008). Another issue discussed in the literature is the method by which actual trait scores are constructed, these range from simple sum scores, to more elaborate linear combinations (factor scores), to the more recent concept of fuzzy sets, where a consumer is identified into a consumer segments using a score ranging between $0 - 1$ (Fiss, 2011). We refer the reader to Ragin (2000) for an overview.

The difficulties in measuring psychological traits demonstrate themselves not only by the large literature on the topic, but also manifest themselves through concerns regarding validity and reliability. While many scales are internally consistent—as checked using reliability analysis or factor analysis—, the test-retest reliability of (e.g.,) personality traits is often low (Peter, 1979), and it is hard to develop novel instruments that are sufficiently reliable (Santor et al., 1997). Also the validity of traits is often a topic of discussion: for many traits the correlations with behaviors are small (Zanna et al., 1980), and both the construct and external validity of many instruments is debated (see, e.g., McCrae and

Costa Jr, 1994). Thus, even when ignoring the costs involved in administering a survey to every customer, finding trait measures that are reliable and valid is non-trivial.

On the positive side, psychological traits are often believed to be context independent (Santor et al., 1997; McCrae and Costa Jr, 1994). Thus, many traits are considered stable—at least to some degree—over time and circumstances. This makes psychological trait scores potentially extremely valuable additions to our CRM data: while consumer preferences might change rapidly over time, personality traits endure and can potentially be used to guide customization in a multitude of situations. However, we have to highlight that context—and thus also the context-dependency of a trait—is not binary but rather continuous: personality traits that predict (purchase) behavior for one product category might generalize to another product category (and hence be robust to relatively small contextual changes), but might hardly prove valuable when trying to understand the health behaviors of that same consumer; the more distinct the context, the less likely the measure generalizes. A large body of work on measuring psychological traits has focused on de-contextualized measures of traits, favoring context independence over performance in specific situations (Furnham and Procter, 1989). Recently however, researchers both in marketing and psychology seem to focus on trait scores that might be more prone to change over contexts at the benefit of performing better—in terms of predicting behavior—within a (related) context (Shobeiri et al., 2013).

Discussions of context dependence and external validity of traits have lead to a distinction in the psychological literature between so-called *operative* and *meta-judgmental* measures of a trait (Bassili, 1996). This distinction is best understood by borrowing from (Polanyi, 2012) and (Jacoby and Kelley, 1987; Jacoby et al., 1989) the distinction between psychological processes as “tools” and as “objects”. Psychological processes serve as *tools* when they are committed to accomplishing a task, such as in the decision to purchase a product. Psychological processes serve as *objects* when they are themselves the focus of attention, such as when respondents attempt to explain how they arrived at the decision to purchase a product. When filling out a survey, customers treat psychological processes as objects; they reflect on their own mental process. However, when responding to a marketing message, for example by clicking on a product, the psychological process is used as a tool to make the decision. Operative measures are likely to be more context dependent, since the behavior is manifest within a specific context, but at the added benefit of being more predictive of future behavior in that context.

Operative measures inspire the active elicitation of consumer responses to marketing messages to obtain estimates of psychological traits. Thus, we can confront consumers with (e.g.,) messages designed to appeal to different cognitive styles, personality traits (for examples see Hirsh et al., 2012), or susceptibilities to persuasive messages (Jarvis and Petty, 1996; Kaptein et al., 2012). Based on consumer responses to these messages we can obtain *operative* measures of traits that can be used to customize communication.

The current work focuses on differences in the ability to predict future behavior using trait-scores obtained using either operative or meta-judgmental measures. To illustrate, we detail how a firm could obtain trait-scores using either method. Suppose a firm intends to measure the extraversion (Gosling et al., 2003; Hirsh et al., 2012). The meta-judgmental approach to obtaining these scores for all customers in a CRM system is as follows:

1. The firm finds validated scale to administer to its consumers. Often, the scale comes at a cost, precisely because of the difficulties in developing good scales as described above.

2. The firm administers the survey. In practice, often only a small portion of customers in the CRM system is invited to fill out the survey, and trait scores for this sample are computed.

3. The firm generalizes the trait scores; if, for example, all the extraverts in the sample happen to be customers from a certain geographical region who bought a certain product we generalize and impute an “extravert” label to similar customers.

4. Finally, the labels “extravert” and “introvert” are used to direct a communication campaign.

Obviously, the firm needs to be able to a) reach out to consumers to fill out the scale, and b) effectively generalize the scores to all the entries in its CRM database; this imputation step might be non-trivial.

We contrast this method with the possible use of operative measures. Note that for a firm to be able to obtain operative measures it has to a) have recurrent interactions with its customers, and b) be able to directly measure the behavioral response of a customer. This situation is likely applicable for online stores: consumers often visit multiple pages of a store, and each page provides an opportunity to interact. Subsequently, the behavioral response is easily logged. If the firm has these opportunities, obtaining operative measures is, in theory, straightforward:

1. The firm designs (a minimum of) two versions of their messages; one appealing to introverts and one appealing to extraverts. Specifically in this case, a product pitch appealing to either personal benefits or outside appearance could elicit different responses from introverts and extraverts.

2. The firm displays the messages randomly to her customers and monitors the behavioral responses; clicks on product pitches that stress personal benefits would lead to an increased introversion score and vice-versa.

3. As customers interact with the firm, every click on a product represented using a distinct appeal—note that the product presentations are designed *explicitly* to elicit responses by consumers with different trait scores—contributes to an updated score in the CRM system.

The above description highlights two important issues. First, to obtain operative measures we do not merely observe consumer behavior; rather, we specifically design our IMC messages to elicit behavioral responses that differ for consumers with different trait scores. Note that in this sense operative measures also stand apart from recent (successful) attempts to predict psychological traits by tracking online behavior: while Kosinski et al. (2013) managed to predict personality scores based on Facebook likes, we would consider this the imputation step of a meta-judgmental measure—since we merely predict scores based on shared characteristics between people—rather than an actual operative measure. The pages that are "liked" have not been explicitly designed to elicit trait scores. Second, the process description illustrates that the costs involved obtaining traits scores using either method depend heavily on the current opportunities of the firm; we consider these cost in more detail on the discussion section.

Strongly related to the idea of operative versus meta-judgmental measures is the notion of implicit and explicit measures of traits as used in the Human-Computer Interaction literature (Kaptein et al., 2015). Here, *explicit* measures are those that are obtained by explicitly asking users[1] to reveal their traits, often using a survey. *Implicit* measures on the other hand are obtained by deducting a score based on behavioral observations of users. This literature is rightfully concerned with the privacy and trust implications that the latter method might have: when obtaining explicit scores there is some form of consent from the users since she actively provides the information; this is not so for implicit measures. The same seems to apply to meta-judgmental and operative measures, an issue we also discuss further below.

Finally, one could wonder about the context dependence of operative and meta-judgmental measures. Consider again the extraversion score detailed above; while likely the survey instrument provides a context independent measure of extraversion, the extraversion score derived from observing the trait being "in play" in an online store clearly is tied to a context. One could debate which of the two is most useful; if the firm intends

[1]Its common in the literature to refer to their research subjects as "users" since the literature is concerned with the usage of interactive systems.

to communicate with its customers solely in the context of (online) selling, the later might be preferred.

The process of customization

Before developing our hypotheses we detail how measures of consumer traits are used in the customization process. Currently, the process of customization is often relatively static: we first collect customer information, and subsequently we profile customers (Schubert, 2000; Peltier et al., 2003) or estimate the effect of specific messages on segments (Kaptein and Parvinen, 2015). Next, we select a message for a distinct segment. Key to this process is the estimation step: we aim to select those message which we deem most effective for the customer segment.

However, when using operative measures the process of customization becomes inherently *dynamic* since trait scores are derived from the observed behavior in previous interactions. Figure 2 shows how the static customization path is changed into a dynamic "loop". In the dynamic loop a firm selects a message partly to elicit a response. This response is subsequently used to update the information regarding the customer and to improve predictions. The better the prediction of message succes, the better the firm is able to select an effective future message (Kaptein and Parvinen, 2015).

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Hypotheses

Based on the literature reviewed above, we now develop our hypotheses. First, we hypothesize the following

Hypothesis 1: *In an online selling context, stimuli can be created that elicit distint behavioral responses from distinct customers and allow a firm to compute (operative)* *trait-scores.*

This first hypothesis formalizes that the process as described above is feasible. We will examine this hypothesis by carrying out the process ourselves for a specific trait and demonstrating the validity of the obtained scores.

Second, in the psychological literature it is well-known that participants find it cumbersome to reflect on their own psychological processes (Bassili, 1996); although meta-judgmental measures obtained using surveys are widespread, often the predictive validity of these measures is limited. One reason for the low predictive validity of meta-judgmental measures is their generality. On the other hand, operative measures are obtained within a specific context; a consumer's response to an advertisement appealing to extraverts is inherently tied to the context. As such, while meta-judgmental measures might generalize to more contexts, we believe that operative measures are more effective in predicting future behavior within a specific context. This leads us to hypothesize the following:

Hypothesis 2: *Operative measures outperform meta-judgmental measures when used for predicting customer behavior within (a similar) context.*

Finally, we would like to stress the dynamic nature of operative measures; operative measures are refined and improved as more and more interactions with consumers accumulate. Hence, we formulate the following hypothesis:

Hypothesis 3: *The improvement in performance of operative measures over meta-judgmental measures increases as more and more responses are collected from individuals.*

In the current work we limit ourselves to examining a single trait; that of susceptibility to persuasive strategies (Kaptein and Eckles, 2012). In the next section we detail the use of persuasive messages in IMC and describe why this trait is interesting for customizing IMC campaigns.

Customizing Persuasive Strategies

Researchers in consumer marketing and psychology have been studying the effects of persuasive messages (e.g. Cialdini and Trost, 1998; Cialdini and Goldstein, 2004). Different taxonomies of persuasive messages have been created (e.g., Cialdini, 2001; Fogg, 2009; Rhoads, 2007), and numerous demonstrations of the effects of persuasive messages on people's attitudes (Crano and Prislin, 2006) and behaviors (Cialdini, 2005) exist. In this paper we examine the effect of customizing persuasive strategies using a subset of the strategies identified by (Cialdini, 2001). We focus on messages implementing the following strategies:

- The *authority* strategy: When an authority figure tells people to do something, they typically do it (Milgram, 1974; Blass, 1991). Consumers are therefore frequently faced with authority endorsements of products such as "expert review". Authority is considered a form of social influence (Kelman and Hamilton, 1989; Martin and Hewstone, 2003), which is effective because some level of responsibility and obedience to authority is essential for the existence of every social community (Modigliani and Rochat, 1995).

- The *consensus* strategy: When individuals observe multiple others manifesting the same belief or behavior, they are more likely to believe and behave similarly (Ajzen and Fishbein, 1980; Goldstein et al., 2008; Zhu and Zhang, 2010). Multiple processes have been posited to explain the effectiveness of the consensus strategy: Asch (Asch, 1956) ascribes the observed effects to mere conformity, whereas others postulate that its implementation constitutes informational influence, serving as "social proof" (Hardin and Higgins, 1996).

- The *scarcity* strategy: Assumed scarcity increases the perceived value of products and opportunities (Cialdini, 2001), consequently advertisers and salespeople tend to use phrases such as "limited release", and "while supplies last"(Lynn, 1991). Multiple psychological processes have been put forward in order to explain the effects of scarcity. The most prominent of these, based on commodity theory (Brock, 1968), asserts that humans desire scarce products because the possession of such products produces feelings of personal distinctiveness.

Large effects of the use of persuasive strategies have been found. However, researchers have also found evidence for heterogeneity in the effects of persuasive messages (Eagly, 1981; Haugtvedt and Petty, 1992; Cacioppo and Petty, 1982; Kaptein and Eckles, 2012; Chocarro et al., 2015). Hence, there is a clear indication that an interaction between psychological traits of consumers and their responses to persuasive strategies exists. We include the most prominent of these traits in our study:

- *Need for Cognition (NfC)*: a trait quantifying a person's willingness to think which is known to interact with the effectiveness of persuasive messages. (Cacioppo and Petty, 1982).
- *Personality*: Hirsh et al. (2012) showed a direct relation of Big Five personality traits to responses to distinct persuasive appeals.
- *Susceptibility to persuasion*: Specifically for the strategies of authority, consensus and scarcity, Kaptein et al. (Kaptein et al., 2012) developed a survey instrument to measure an individuals tendency to comply to messages implementing these strategies.

We have to note that a large number of traits could have been selected for inclusion in this work, as the literature on attitudes, motivations, and traits is large (see, e.g., Larose et al., 2001; Ko et al., 2005; Sundar and Limperos, 2013). While we limit our scope to the context of persuasive strategies, other options that could be conceived include:

- Personality: Many meta-judgmental measures for personality exist, famous amongst which is the Big Five (Gosling et al., 2003). However, Hirsh et al. (2012) showed that different product representations appeal to consumers with different personality traits; effectively demonstrating that an operative measure could be obtained.

- Cognitive style: A standardized survey instrument to measure cognitive style exists (see, e.g., Huber, 1983). However, Hauser et al. (2009) demonstrated that the click behavior of consumers can be used to tailor webpages to consumers cognitive style; hence in effect demonstrating the utility of an operative measure.

- Locus of control: A consumer's locus of control relates to the inclination to attribute events to herself or to the outside world. For this trait survey measures exist (Ajzen, 2002), but recently health motivation applications have been developed in which a users' locus of control is derived from her response to specifically tailored messages (Van Dantzig et al., 2013).

Method

We setup an online study to measure consumer responses to persuasive messages (to obtain the operative measures) and administered a number of questionnaires (to obtain meta-judgmental measures). In the study participants were asked to fill out the survey, and they were asked to state their Willingness to Pay (WtP) for nine different products. Each of the products was pitched using a different persuasive strategy (either "none", "authority", "social proof", or "scarcity").

Ethics Statement

Students participating in a course on questionnaire design were asked to fill out our online survey.[2] Students were informed in that their answers would be used anonymously. The first item of the survey addressed whether or not students were willing to participate and the second queried whether their answers could be included for usage in scientific

[2]The survey was administered in Dutch. An English translation of the items used in the current study is available from the authors upon request.

studies. Only those students who answered both questions affirmative were included. The survey was carried out online, and hence there was no signed consent form. However, the inclusion of the statement of the participants to be willing to disclose their data for scientific purposes (anonymously), and the previous excemption of the Stanford IRB to a similar study protocol (which was carried out using a similar consent procedure), was deemed sufficient.

Participants

Participants were $N = 283$ students enrolled in social science courses who participated for partial course credits (117 men, $M_{age} = 21.7$, $SD_{age} = 1.9$).

Procedure

Participants filled out a survey that addressed demographics and subsequently measured several traits using standardized scales. Next, participants were instructed that they would be presented with 9 books and that they would be asked to evaluate these books. Participants were sequentially presented with 9 advertisements each containing a cover of a book, the name of the author, and the recommended price (see Figure 3). The books all fell in the same price range ($14 -$16) and subjects were all science-related. Each book was accompanied with a button stating the "reason" why it was selected. These reasons implemented the consensus, scarcity and authority persuasive strategies as well as a control version in which the book was presented without any reason. The consensus implementation was "World-wide bestseller!", the scarcity implementation was "Almost out of stock!" and the authority implementation was "The NYT recommends!".

Each persuasive strategy was displayed twice or thrice and there were two books displayed *without* a persuasive message. The order of books, as well as the order of the labels and the matching of labels and books were randomized. After viewing a book, participants indicated how much they were willing to pay in euros.

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Measures

Obtaining Meta-judgmental Measures. We included a 30-item measure of the Big Five personality traits (Gosling et al., 2003); Extraversion (5 items, $\alpha = 0.76$), Conscientiousness (5 items, $\alpha = 0.91$), Agreeableness (5 items, $\alpha = 0.83$), Openness to Experience (5 items, $\alpha = 0.75$) and Neuroticism (5 items, $\alpha = 0.82$). For each of the five personality traits a composite score was computed by means of the factor scores (using Principal Axis Factoring). Personality was included since it has been shown to relate to responses to persuasive appeals (Hirsh et al., 2012). We also administered the 18-item measure of Need for Cognition (NfC) ($\alpha = 0.82$) for which sum scores were computed (Cacioppo and Petty, 1982). NfC is a widely used measure in the literature on persuasion and social influence and identifies an individual's "tendency to think". Those with higher scores are said to comply less to persuasive appeals. Next, participants were presented with the 30 items of the Susceptibility to Persuasion Scale (Kaptein et al., 2012) that measures people's susceptibility to distinct persuasive strategies. Factor scores were computed to obtain a composite scores for the susceptibility to Scarcity (5 items, $\alpha = 0.62$), Authority (4 items, $\alpha = 0.75$) and Consensus (4 items, $\alpha = 0.75$) sub-scales. Finally, participants were asked about their age, gender, ethnicity, living situation and academic major.

Obtaining Operative Measures. The operative measures were derived from the amount of euros that participants were willing to pay (WtP) for each of the books. We used a hierarchical model to estimate trait scores based on the measured WtP. While details of this estimation procedure are described in the analysis section, here we provide some intuition. Table 1 gives the responses of two customers ("A" and "B") to the 9 books. Displayed are both the persuasive strategy that accompanied the book, as well as the participants WtP. From these responses we can obtain a trait score: First, we compute the participants average WtP for books that are presented without persuasive strategies (neutral): $(12 + 13)/2 = 12.5$. Next, we compute the average WtP for books presented with the authority strategy: $(15 + 16 + 18)/3 = 16\frac{1}{3}$. The difference between these two provides an estimate for the participants trait score on "susceptibility to Authority": $16\frac{1}{3} - 12.5 = 3.83$. In a similar fashion we can obtain an estimate of the susceptibility to authority trait for customer B which is -6.5. Thus, by analyzing the behavioral responses of consumers we can obtain scores on psychological traits.

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The estimation procedure described here is infeasible for several reasons: first, the obtained scores are not standardized and are thus hard to interpret. Second, the estimation of the averages based on only two or three observations is very noisy. Both of these issues can be overcome by using an hierarchical model. In this model the noise in the individual level estimates is reduced by "borrowing strength" from other participants, and the scores are computed in units of standard deviation(s) from the mean. The exact model used is presented below. Figure 4 shows a scatterplot of the (operative) trait scores obtained in our study.

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Analysis and results

The study provided us with meta-judgmental measures of customers traits (personality, susceptibility to persuasive strategies, etc.), and with a small set of operative measures. In this section we examine the utility of these measures in predicting the effect of future messages. The default approach in interactive marketing would be to identify the dependent variable, in our case WtP, cluster or segment customers based on the trait scores, and see how the segments relate to WtP. Our approach is similar in spirit, but slightly more involved: First, we do not segment customers, but rather work with individual scores of customers throughout. We make this choice since segmenting would needlessly reduce the variance. Second, instead of correlating the trait scores with the observed WtP, we focus on predicting future WtP; we omit the last time point of the observed data when creating the trait scores, control for customers overall WtP, and try to predict this last datapoint. We believe this method is less prone to overfitting, and more informative of the actual size of the effect, than reporting simple correlations.

Manipulation check

As expected, we find a positive effect of the use of persuasive strategies: we find an average WtP of 10.93, ($SD = 7.57$) for books presented without a persuasive strategy, while the average WtP for books presented using the scarcity, 11.13, ($SD = 7.92$) , authority, 11.56, ($SD = 8.74$) , and consensus, 12.45, ($SD = 8.93$) , strategies are all higher. The main effect of the use of persuasive messages is statistically significant, $F(3, 2563) = 3.87$, $p < .01$. This replicates earlier findings (see, e.g., Kaptein and Eckles, 2012) and shows that our messages are successful.

Computation of out-of-sample predication error

For each participant $\texttt{id} = 1, \ldots, N = 283$ we have a number of meta-judgmental measures (e.g. `Openness`, and `Neuroticism`), and we have also have $\texttt{time} = 1, \ldots, T = 9$ responses to products. These responses are to $\texttt{Products} \in \{1, \ldots, 9\}$, presented with a $\texttt{Strategy} \in \{$“Neutral”, “Social Proof”, “Scarcity”, “Authority”$\}$ and we observed willingness to pay (`WtP`). Our aim is to predict the response of participants at $\texttt{Time} = 9$ *out of sample*: hence, we try to predict the `WtP` at $\texttt{Time} = 9$ for a specific participant without using this specific observation itself to fit the model. As the main comparison criterion we use the mean out of sample squared prediction error (OSE). OSE is defined as $\frac{1}{N}\sum(y_i^* - y_i)^2$, where y_i^* is the *predicted* WtP at time 9 and y_i the observed WtP.

To evaluate the OSE of the meta-judgmental measures we use a well-known ten-fold cross validation approach (Hastie et al., 2013): we fit a model predicting $\texttt{WtP}|T = 9, \ldots$ using the different traits scores of a randomly selected subset of 90% of our participants. We than use the estimated coefficients from this model to predict $\texttt{WtP}|T = 9$ for the left out 10% of participants and compute the OSE. We repeat this process $m = 100$ times. To evaluate the OSE of the operative measures we take a slightly different approach: here we predict $\texttt{WtP}|T = 9$ using *only* participants previous responses. We fit a hierarchical model to estimate the effect of each strategy for each subject. This model *omits all descriptors of participants* and uses *only* the trait scores derived based on the previous responses. Note that by using a hierarchical model we do pool together information over multiple participants; hence predictions are not solely based on the datapoints of one participant, but are also informed by the ratings of the other participants. This information would be available in practice for those using operative measures. To enable direct comparison with the cross-validation procedure, the operative model(s) are also fit on a random selection of 90% of the participants of the original dataset. Subsequently, the OSE is computed over 10% of the dataset to provide a comparable sampling variability. This approach achieves two goals: first, the number of cases used for the prediction is the same in each of the two settings. Second, the number of predicted values is this same in each case.

Prediction Error using Meta-judgemental Measures. To predict the response to the 9^{th} product using meta judgmental measures we start by using a very elaborate model using all the traits measured in the study. In this model the outcome is predicted using the following model:

$$
\begin{aligned}
y_i = &\beta_0 + \beta_{1,\ldots} Strategy + \beta_{\ldots} Gender \times Strategy + \beta_{\ldots} Age \times Strategy + \\
&\beta_{\ldots} Extraversion \times Strategy + \beta_{\ldots} Conscientiousness \times Strategy + \\
&\beta_{\ldots} Agreeableness \times Strategy + \\
&\beta_{\ldots} Openness \times Strategy + \beta_{\ldots} Neuroticism \times Strategy + \\
&\beta_{\ldots} NfC \times Strategy + \beta_{\ldots} Scarcity \times Strategy + \beta_{\ldots} Authority \times Strategy + \\
&\beta_{\ldots,k} Concensus \times Strategy + \\
&+ \lambda_{j[i]} + \nabla_{l[i]} + \epsilon
\end{aligned}
$$

where $\beta_{\ldots}$ is the estimated coefficient of the effect (which are many, given the dummy coding of `Strategy`), $\lambda_j \sim \mathcal{N}(0, \sigma_j^2)$ and is a random effect of `Strategy`, $\nabla_l \sim \mathcal{N}(0, \sigma_l^2)$ and is the random effect of `Product`, and $\epsilon \sim \mathcal{N}(0, \sigma_\epsilon^2)$, the error variance. With the interactions terms denoted using "×" we mean that we include both the interaction and the main effects. The terms "Scarcity", "Authority", and "Consensus" refer to the scores obtained on the susceptibility to persuasion scale. We refer to this model as *Model 1*.

We use Model 1 as a baseline. However, due to the large number of parameters this model likely overfits the data (Cf. Gaber et al., 2005). Hence, we also explore two alternatives: First, we examine a model in which we use a series of model comparisons using all possible sbusets of the above model and select the model with the lowest BIC: we selected this model using the `MuMIn [R]` package. The selected model, *Model 2*, is:

$$\begin{aligned} y_i = &\beta_0 + \beta_{1,\ldots}Strategy + \\ &\beta_{\ldots}(Extraversion \times Strategy) + \\ &\beta_{\ldots}Agreeableness + \\ &\beta_{\ldots}NfC + \\ &\beta_{\ldots}Scarcity \times Strategy + \\ &\beta_{\ldots,k}Concensus + \\ &\lambda_{j[i]} + \nabla_{l[i]} + \epsilon \end{aligned}$$

Finally, we also examine the use of regularization (see Hastie et al., 2013, for a discussion). We use the random effects Lasso as defined in `GLMMLasso` to subset the number of predictors. Since the `GLMLasso` selects a different model for each of the 100 iterations we do not write out the models explicitly. We coin this approach *Model 3*. Note that in each of these models the average behavior of customers is included through the random effects; hence these models contain demographic data, psychographic data, *and* behavioral data to provide.

Prediction Error using Operative Measures. We use `WtP`$|t = 1, \ldots, t = 8$ and the structure of the messages, to obtain scores on the operative measures and predict `WtP`$|T = 9$. The model can be written out as follows:

$$y_i = \beta_{j[i]} X_{j[i]} + \nabla_{l[i]} + \epsilon \tag{1}$$

In this specification $\beta_{j[i]}$ is a vector containing the estimated effects for each of the persuasive strategies where $\beta_{j[i]} \sim \mathcal{MVN}(\beta_0, \Sigma)$. Thus, there is a random effect (over participants) for each strategy. We take the Maximum a Postriori (MAP) estimates of the individual level coefficients as the operative trait scores. As above, $\nabla_{l[i]}$ is the random effect for the products.[3]

[3]Note that the random effects models allow for "shrinkage" estimation, a procedure closely related to Bayesian modeling in its spirit by making distributional assumptions regarding distinct batches of effects.

Testing of our hypotheses

Our first hypothesis concerns the ability to create operative measures: Figure 4 displays the estimated operative measures for consumers included in our study resulting from the procedure described above as applied to the full dataset. This Figure by itself does not provide a formal test of the ability to quantify meaningful variance in consumer traits however, such a test can be provided by looking at the variance components of the model described in Eq. 1. In line with earlier work (Kaptein and Eckles, 2012), we inspect these variance components to quantify the heterogeneity in consumers responses to persuasive strategies. Table 2 displays the estimated fixed effects and random effects. It is clear that the estimated random effects are (comparatively) large; the estimated standard deviations are larger than the main effects. A formal test comparing a model without the random terms for the strategies with the larger model including random strategy variation rejects the null-hypothesis of zero variance components and prefers the more complex model, $p < .001$, $\chi^2 = 113.09$; this analysis shows that meaningful variation in consumer responses to persuasive messages can be elicited and confirms hypothesis one.

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Place Table 2 about here

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To test our second hypothesis, Table 3 present the performance in terms of OSE of the models included in our study. It is clear that the OSE of the model that uses operative measures is (magnitudes) lower then that of any of the models using only meta-judgmental measures ($p < .05$ in each case using pairwise t-tests with Bonferroni corrections). This confirms our hypothesis that actively elicited behavioral responses can be more effective in

This approach is favored by a number of marketing scholars aiming to estimate the effects of distinct messages (see, e.g., Ansari and Mela, 2003; Kaptein and Eckles, 2012). We are however not using a fully Bayesian approach; the current approach is often referred to as "empirical Bayes" since the prior distributions are determined from the data. (Gelman and Hill, 2007).

predicting future responses than meta-judgmental measures.

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Place Table 3 about here

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To examine hypothesis three, we compare the performance of the best performing meta-judgmental model (Model 3) with the performance of the operative measures as more and more data are concerned. Table 4 shows the obtained difference in OSE between the use of operative measures based on $T = 3, \ldots, T = 8$ observations and meta-judgmental measures. Confirming our hypothesis, we see that the difference in model performance increases as more observations become available.

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Place Table 4 about here

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To conclude, despite elaborate efforts to lower the OSE of the meta-judgmental measures using model selection and regularization, operative measures outperformed the meta-judgmental measures in our context. This supports our hypotheses and opens up the door to dynamic customization using psychological trait scores derived from the behaviors of customers. We distribute the annotated dataset resulting from our experiment with this paper to allow others to improve on our prediction(s). The dataset can be retrieved at `http://dx.doi.org/10.7910/DVN/OXDAE9`.

Discussion

In this paper we examined the use of operative- versus meta-judgmental measures for customization. We have shown that operative measures outperform meta-judgmental measures when it comes to predicting consumer behavior. While our result might be specific to customizing persuasive messages, we content to have shown the potential of using operative measures in marketing communication: a well-chosen selection of messages can be used to obtain psychographic measures of consumer traits.

Theoretical implications

Our study has a number of theoretical implications. First of all, the stellar performance of operative measures raises a number of questions regarding the validity and reliability of meta-judgmental measures and operative measures. In our study, the meta-judgmental measures of susceptibility to persuasion, even when combined with a large number of alternative trait measures, seems to have a low predictive validity. However, a number of these measures, such as personality using the Big Five, have previously showed reliable and valid in other settings (Santor et al., 1997; Gosling et al., 2003). Perhaps our field has focused too much on internal consistence, test-retest reliability, and construct validity as opposed to predictive validity? On the other hand, operative measures, which can be seen as reflective measures of traits since its likely that the trait causes the observed behavior (Coltman et al., 2008), beg further scrutiny; high predictive validity is an asset but the test re-test reliability, and the construct validity of operative measures remain open questions.

Another challenge is highlighted by our first hypothesis; while we have managed to create relatively simple marketing messages that elicit distinct responses from consumers, theories motivating different psychological traits often do not link one-to-one with marketing messages. We have provided suggestions, e.g., changing from textual to visual product presentations as a means of eliciting responses from consumers differing in their cognitive style (Huber, 1983), but for a large number of psychological traits their operationalization in marketing messages is less clear-cut. It is thus a theoretical challenge to move from the survey items now used to marketing messages that allow operative measurement. Here, a new discipline of developing such operative measures could emerge: how can we create “item pools” and select the best “items” to created a reliable and valid measure when our items are themselves in fact marketing messages?

Next to creating operative measurement instruments, our study also raises questions regarding the interactions between traits: when collecting meta-judgmental measures, often a large number of items are administered to, while the number of observations involved in constructing an operative measure is inherently limited by the number of interactions. Because of this limitation, it becomes interesting to see whether multiple traits can be queried simultaneously using a single marketing message. This also enourages us to reflect back on our current—and ever growing—set of psychological traits: if we are in a way “forced” to limit our selection, which traits are then most useful?

The distinction between operative and meta-judgmental measures raises interesting questions regarding the context dependency of trait scores. Traditionally, psychologist have searched for “context independent” scores in the sense that these are, as much as possible, a property of the person as opposed to the person-environment combination. However, no binary distinction between the two exists; to a lesser or greater extend the environment will have an impact on the manifestations of a trait, and possibly even—in a formative sense (Cenfetelli and Bassellier, 2009)—influence the trait itself. The current work highlights a theoretical challenge of creating operationalizations of context and context dependency that are useful for IMC: one could argue that we are looking for trait scores that inform us about consumer responses to marketing messages, not for trait scores that are useful in a broader context but provide less clarity in our own domain. We need to understand this trade-off.

Operative measures, since they are often obtained implicitly (Kaptein et al., 2015), also raise a number of theoretical questions regarding the perceptions of privacy of consumers and their trust in the firm. While customers have, in recent years, become aware of the fact that product preferences are derived from browsing behavior, it remains to be seen whether deriving psychological traits form actively elicited behavior is feasible. We encourage firms to be transparent about their data collection, and to allow customers to inspect, alter, or delete estimated trait scores, as a way of ensuring consumer trust. While the short term prediction of future behavior seems to favor operative measures, longer term effects on trust and privacy are unclear. The current study re-emphasizes the importance of theories relating short term consumer behavior to long term consumer engagement and satisfaction and the mediation of these processes by perceptions of privacy and trust.

Managerial implications

Our current study potentially impacts IMC practice. At minimum, we have demonstrated an alternative method—as opposed to the standard survey practice—by which CRM systems can be enriched with psychological trait scores. The great predictive performance of these scores should highlight the possible importance of our method. However, the costs and efforts involved in obtaining operative measures will differ tremendously from firm to firm. For firms who operate largely online, have a habit of (e.g.,) AB testing marketing messages, and have the ability to store and process behavioral responses, obtaining operative traits measures boils down to a fairly limited effort of consciously designing marketing messages such that these elicit different responses from different customers. We have provided a clear starting point and hope that additional operationalizations will follow. On the other hand, for those companies who do not have these facilities in place, setting up such an infrastructure might be more costly than obtaining meta-judgmental measures.

The practice of obtaining operative measures raises also raises practical issues regarding privacy and trust. The practice of imputing psychological trait scores based on behavioral traces (such as carried out by Kosinski et al., 2013) is heavily debated in the popular media, and thus explicitly designing marketing messages to elicit behavior that allows a firm to obtain trait scores could easily be even more debatable. On the other hand, compared to surveys, operative measures do reduce the costs of the customer—since no explicit actions are needed—and thus might eventually be preferred by customers as long as they perceive the resulting customization to be meaningful.

Limitations and future work

Despite highlighting the potential of operative measures, our work has a number of limitations. First of all, we feel the use of willingness to pay—as opposed to actual payments—needs further scrutiny: our study should be replicated using actual behavioral outcomes. Next, our study seemingly benefitted the performance of operative measures by using the operative trait scores to predict future customer behavior in the exact same context. We have discussed the theoretical importance of further investigating the role of context, but would like to see replications of our work in which the performance of operative and meta-judgmental trait scores is investigated for increasingly more distinct contexts: our study could be replicated exploring consumer responses in a different online stores, for a different product categories, or, in the extreme case, even outside the marketing context.

Finally, while we have provided several examples of traits that might be measured operatively, future work needs to create the actual stimuli that elicit behavioral responses that allow firms to infer trait scores. How exactly would we create (e.g.,) emailed marketing messages such that they appeal differently for customers with (e.g.,) different levels of agreeableness? Furthermore, even if we manage to design such messages, how can we judge the construct validity and reliability of the resulting scores? We hope the current paper encourages future work in this direction.

To conclude, we have demonstrate the potential usefulness of obtaining operative as opposed to meta-judgmental measures of consumer traits. Furthermore, we hope our work inspires a novel avenue for theoretical research into the reliability and validity of operative measures as opposed to meta-judgmental measures.

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