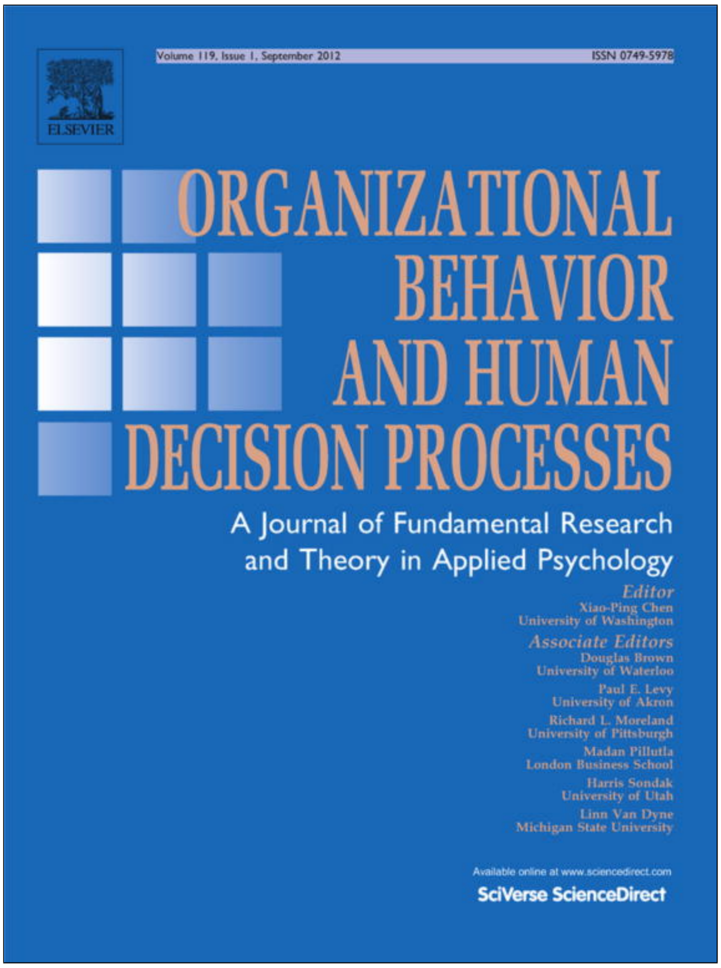
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Attribute-value functions as global interpretations of attribute importance

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ABSTRACT

In order to better understand decision maker's perceptions of the importance of attributes, Goldstein (1990) differentiates between global and local interpretations of attribute importance. While the appreciation for the distinction is growing, research on the relationship between measures of global and local importance is inconclusive. We believe that these inconclusive findings are caused by operationalizing global attribute importance with single-point measures that implicitly assume that the global interpretation of attribute importance linearly depends on the relevant range of context-specific attribute levels. To address this, we propose to operationalize the global interpretation of attribute importance by estimating decision makers' attribute-value functions. Two empirical studies demonstrate that the shape of attribute-value functions changes from concave to convex with global attribute importance. Furthermore, the steepness of these functions increases with global attribute importance while the diminishing sensitivity decreases. Finally, it is demonstrated that the inconclusive findings about the relationship between common, single-point measures of global and local attribute importance is driven by non-linearities in decision makers' attribute-value functions. The results suggest great promise for future research on using decision makers' attribute-value functions for measuring the importance of attributes.

Introduction

Attributes derive importance from their ability to help decision makers achieve important personal goals (Van Harreveld & Van der Pligt, 2004). Attributes that help achieve important personal goals will be perceived more important than attributes that do not contribute to achieving these goals (Batra, Homer, & Kahle, 2001). Being able to measure and identify important attributes is critical when evaluating and screening opportunities, ideas, and alternatives. Take for instance an HR manager interested in creating attractive job offers based on salary and number of vacation days. To find out which attribute is more important, the manager could ask current employees to rate the importance of salary and the number of vacation days. Alternatively, the HR manager could ask the employees to make a series of trade-off judgments and infer attribute importance. However, research has shown a lack of convergent validity between both methods for measuring attribute importance. For instance, Fischer (1995) finds that study participants placed more weight on the salary attribute when making trade-off judgments than when providing direct ratings of attribute importance. In a notable attempt to refute the belief that this lack of convergent validity between different methods for measuring attribute importance is driven by people's lack of insight into their own decision making process, Goldstein (1990) proposes that differences in the perception of attribute importance between decision makers and researchers may be an alternative reason for the inconclusive results. In order to gain a better understanding of decision maker's perceptions of the importance of attributes, Goldstein (1990) differentiates between global and local interpretations of attribute importance. The local interpretation assumes attribute importance to be an assessment that explicitly depends on the range of attribute levels in the stimulus set. The global interpretation considers attribute importance to be a stable characteristic that does not depend on a particular stimulus set, provided that the stimuli do not disturb the person's implicit contextual assumptions. This implies that the global interpretation of attribute importance assumes attribute-importance measures to depend on implicit assumptions about the context-specific range of relevant attribute levels (Srinivasan, 1988). This context-specific range of relevant attribute levels represents the attribute levels decision makers have encountered across a wide range of relevant stimulus sets. Fischer (1995) demonstrates that differentiating between the global and local interpretation of attribute importance improves our understanding as to why preference-based tasks that involve an explicit stimulus-set specific range of attribute levels tend to be more range-sensitive than direct judgments of attribute

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importance that involve an implicit context-specific range of attribute levels.

Although the appreciation for the distinction between global and local interpretations of attribute importance is growing (e.g., Chernev, 2001; Doyle, Green, & Bottomley, 1997; Scholten, 2002; Selart & Eek, 2005), empirical questions regarding both interpretations and their relationship have been raised. For instance, while Fischer (1995) reveals a discrepancy between attribute importance weights inferred from trade-offs and weights inferred from direct judgments of attribute importance, the exact nature of the relationship between these measures remains unclear. Without having an accurate, conceptual understanding of the relationship between global and local measures of attribute importance, scholars and practitioners alike will continue to doubt the validity of existing methods for attribute importance measurement and label perfectly legitimate results as "inconclusive" and "lacking convergent validity". The main contribution of this research is that we propose to operationalize the global interpretation of attribute importance as a function—decision maker's attribute-value function. This attribute-value function reflects decision maker's valuation of an attribute for the context-specific range of relevant attribute levels, relative to the reference point. The benefits are threefold. First, operationalizing the global interpretation of attribute importance as an attribute-value function yields unique insights into the relationship between global and local attribute importance measures. We hypothesize and empirically demonstrate that decision maker's value functions offer a conceptual explanation for inconclusive findings reported in the literature (Barlas, 2003; Srivastava, Connolly, & Beach, 1995), using five global and five local methods for attribute importance measurement. Second, it allows for gaining a more accurate understanding about the relationship between the range of attribute levels in a choice task and local measures of attribute importance, going beyond the range sensitivity principle and value-comparison hypothesis (Fischer, 1995). Finally, attribute-value functions can be used to determine the local importance of attributes in different stimulus sets and they have predictive accuracy in multi-attribute choice contexts.

The importance of attribute-importance measurement

Since the identification of important attributes is essential during any evaluation and screening process, attribute importance measurement is relevant across different business disciplines, including HR (personnel selection), finance and accounting (capital budgeting), operations management (logistics), and for instance marketing (new product development and marketing planning). Accordingly, attribute importance measurement has received attention in a variety of academic disciplines, including organizational behavior (Barlas, 2003; Fischer, 1995; Zhu & Anderson, 1991), management science (Schoemaker & Waid, 1982), social and cognitive psychology (Doyle et al., 1997), new product development (Urban & Hauser, 1993; Van Ittersum, 2012; Van Ittersum & Feinberg, 2010) and marketing strategies (Li & Calantone, 1998).

To facilitate evaluation and screening processes and to minimize the likelihood of making Type I and II errors, it is important to accurately measure the importance of attributes. Type I errors refer to the rejection of an idea when it is a possible success. Type II errors involve decisions that fail to reject an idea when it is a possible failure (Kim & Wilemon, 2002). In the context of new product development process for instance, these errors may result in product development efforts that either overlook attributes that would have enthused consumers (cf., opportunity losses), or focus on attributes that do not prove important to consumers (cf., wasted investment) (Urban & Hauser, 1993).

A wide variety of methods exists to measure the importance of attributes. However, as most recently was documented by Van Ittersum, Pennings, Wansink, and Van Trijp (2007) through an in-depth review of existing literature, the convergent validity—the degree to which different measurements reflect the same construct—among the ten most common methods in behavioral sciences remains low. This lack of convergent validity gives rise to Type I and II errors in decision making.

Goldstein (1990) proposes that the lack of convergent validity of different methods for measuring attribute importance may be due to differences in perceptions of attribute importance between study participants and researchers. In order to explore this, Goldstein differentiates between global and local interpretations of attribute importance and studies which interpretation is most prevalent among decision makers. Instead of assuming that one interpretation is most prevalent, Fischer (1995) demonstrates that the prevalence of both interpretations is determined by the methods used to measure attribute importance. Methods that involve an explicit range of attribute levels (e.g., trade-off judgments) stimulate participants to interpret attribute importance locally, while research methods that do not involve an explicit range of attribute levels (e.g., direct ratings) stimulate participants to interpret attribute importance globally (based on an implicit range of a context-specific attribute levels). Van Ittersum et al. (2007) provide additional empirical evidence for this by re-examining existing research to demonstrate convergent validity among methods that are proposed to measure the global or local importance of attributes, and discriminant validity between methods that are proposed to measure global vs. local importance of attributes. Differentiating between the global and local importance of attributes reduces the apparent lack of validity reported in the literature.

The importance of global and local attribute importance measures

Differentiating between global and local attribute importance measures is not only relevant to reduce the apparent lack of validity among existing methods. It also contributes to reducing the likelihood of Type I and II errors in decision making. For instance, an airline interested in improving the in-flight experience may dismiss the idea of increasing leg space (at higher ticket prices) based on a survey showing that customers rate the ticket price as more important than leg space. However, if they realize that the rating method captures the global but not the local importance of attributes, a second study could be conducted that asks customers to make trade-offs based on an explicit relevant range of attribute levels, allowing the airline to gain insights in the local importance of attributes.

From a managerial perspective, attribute importance is most appropriately defined in relation to its behavioral outcomes (Pennings & Smidts, 2003). Although it is tempting to conclude that the local importance of attributes thus should be the focal component in research, we pose that both the global and local importance should play an important role. First, if one only focuses on identifying attributes that are of local importance, there is a risk of overlooking attributes of global importance. Consequently, "we might increase the leg space in airplanes, but ignore important safety features" (Myers & Alpert, 1968). The overlooked attribute of global importance likely becomes a negative attribute of local importance. Second, the local importance of attributes increases with the global importance of the attribute. Hence, identifying attributes that are of global importance is more efficient than identifying attributes that are merely of local importance (Goldstein, 1990). Third, while attributes of local importance are critical when deciding which one of two products to buy (joint evaluation), attributes of global importance are more critical when deciding whether or not to buy at all (separate evaluation). Since it is generally unknown which decision process applies best and most often, both locally and globally attribute measures should be available. In sum, being able to accurately measure both the global and local importance of attributes is of practical relevance.

Global vs. local interpretations of attribute importance

The importance of attributes arises from their ability to help people reach important personal goals (Van Harreveld & Van der Pligt, 2004). The same personal goal that gives rise to the global importance of an attribute also influences the local importance of an attribute. For example, the local importance of the difference in price between two choices will increase with the global importance of price attribute, which may derive its importance from a personal savings goal (Alpert, 1971). Based on this, it is often assumed that measures of global and local importance of attributes correlate. However, evidence of the relationship between global and local attribute importance remains inconclusive (Barlas, 2003; Srivastava et al., 1995; Zhu & Anderson, 1991). More importantly, it remains unclear why some researchers do find a relationship between global and local measures of attributes, while others do not.

We propose that these inconclusive findings are caused by operationalizing global attribute importance with single-point measures that implicitly assume that the global interpretation of attribute importance linearly depends on the relevant range of context-specific attribute levels. These measures are insensitive to non-linearities in the attribute-value functions decision makers rely upon when responding to attribute-importance questions (cf., Fischhoff, 1991; Keeney, 1992; Svenson, 1996). While common (single-point) measures of global attribute importance are useful to determine the relative importance of multiple attributes in a specific context, they provide little guidance in understanding how the global and local importance of attributes are related. Without this understanding, goods and services may be developed and introduced with attributes end-users deem important in the context (global importance), but not in relevant stimulus sets (local importance). Therefore, we propose to operationalize the global interpretation of attribute importance by means of a decision maker's attribute-value function. Operationalizing the global interpretation of attribute importance as an attribute-value function yields unique insights into the relationship between global and local attribute importance measures. Furthermore, it allows for gaining a more accurate understanding about the relationship between the range of attribute levels in a choice task and local measures of attribute importance. We elaborate below.

Attribute-value functions

The value function of an attribute displays a decision maker's valuation of an attribute for the context-specific range of relevant attribute levels, relative to the reference point. Decision makers' reference points of an attribute are largely determined by the levels of the attribute of the products they are currently using (Bell & Lattin, 2000; Helson, 1964). A decision maker's attribute-value function is context specific and stems from a combination of being exposed to a wide range of relevant attribute levels in daily life (Hoeffler & Ariely, 1999) and the importance of relevant personal goals (Tversky & Kahneman, 1991). With the importance of relevant personal goals, the intensity with which attribute-level information is processed increases (Petty, Cacioppo, & Schumann, 1983) – i.e., decision makers establish their valuation of the attribute levels (Gregory, Lichtenstein, & Slovic, 1993). The outcome is an attribute-value function that decision makers have shown to rely upon in judgment, choice, and for instance when responding to attribute-importance questions (Keeney, 1992; Svenson, 1996).

The overall *shape* of attribute-value functions is influenced by the tendency of decision makers to (1) evaluate attribute levels as gains or losses relative to a reference point (i.e., reference dependence), (2) weigh losses more heavily than gains (i.e., loss aversion), and (3) decrease the marginal valuation of both gains and losses with their sizes (i.e., diminishing sensitivity) (Heath, Larrick, & Wu, 1999; Meyer & Johnson, 1995; Tversky & Kahneman, 1991). Decision-makers' reference dependence, loss aversion, and diminishing sensitivity may produce attribute-value functions with different shapes (see Fig. 1), such as a complete concave value function, an asymmetric S-shaped value function, or a complete convex value function (Kivetz, Netzer, & Srinivasan, 2004).[1] Using apartment size as an example (see Fig. 1), one would expect to find a complete concave (convex) value function in the context-specific range of relevant attribute levels for decision makers who currently live in a small (large) apartment. The rationale for this notion is that the other apartment sizes in the relevant attribute-level range are gains (losses) compared to the decision maker's reference size. For decision makers with a reference apartment size at the intermediate level (i.e., decision maker 2 in Fig. 1), one would expect to find an asymmetric S-shaped value function.

As will be discussed hereafter, the importance of relevant personal goals influences the properties—steepness of slope, loss aversion, and diminishing sensitivity—and overall shape of value functions.

Hypotheses

The work of, amongst others, Fischhoff (1991) and Tversky and Kahneman (1991) suggests that decision makers rely on their attribute-value functions when responding to questions about the global and the local importance of attributes. The attribute-value function can be seen as the underlying mechanism generating decision makers' attribute-importance valuations. Decision maker's attribute-value functions – estimated for the context-specific range of attribute levels – thus form the connection between the global and local importance of attributes.

Decision makers use the difference in valuation associated with the attribute levels involved as an indicator of how important an attribute is (Fischer, 1995). Methods that provide an explicit range of attribute levels (e.g., swing-weight method, trade-off method) stimulate decision makers to interpret attribute importance locally: decision makers rely on their attribute-value function to assess the difference in valuation between the best ($v(x_a^*)$) and worst ($v(x_a^\circ)$) attribute level in the stimulus set and use that information to respond to attribute-importance questions (see Fig. 2).

Methods that do not provide an explicit range of attribute levels, but instead merely present information about the context, stimulate decision makers to interpret attribute importance

[1] Research has shown that decision makers can have a complete concave or complete convex value function (Bell & Lattin, 2000; Kivetz et al., 2004; Pennings & Smidts, 2003). It could be argued, though, that all attribute-value functions are S-shaped, as long as the range of attribute levels studied is increased far enough, and that observing concave and convex functions is merely an artifact of the range of attribute levels studied. However, decision makers develop a value function for the context-specific range of relevant attribute levels. Decision makers who know they cannot afford a rent of $1500 will not process that information in detail (Gregory et al., 1993; Petty et al., 1983). Hence, eliciting decision makers' valuations for attribute levels outside the relevant range of attribute levels yields invalid and unreliable results. Furthermore, collecting information from outside the context-specific range of relevant attribute levels (i.e., irrelevant attribute levels) is not of interest to managerial decision makers. Moreover, it would be inconsistent with the context-specific interpretation proposed by Goldstein (1990).

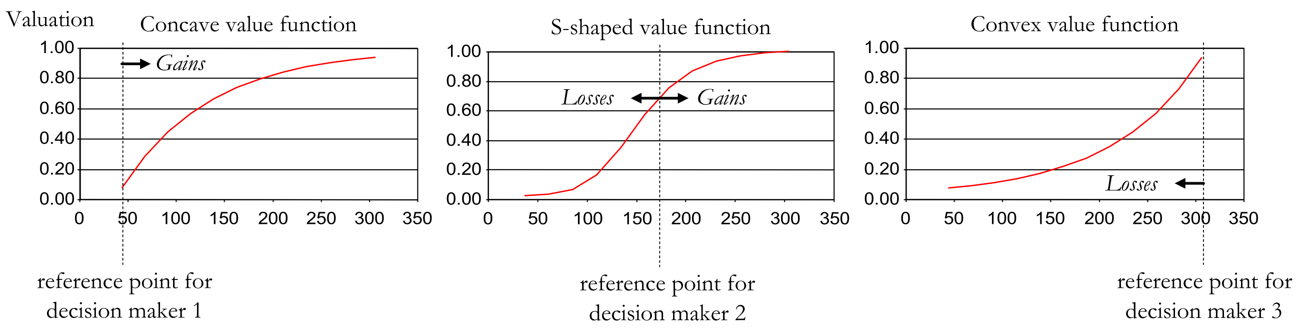
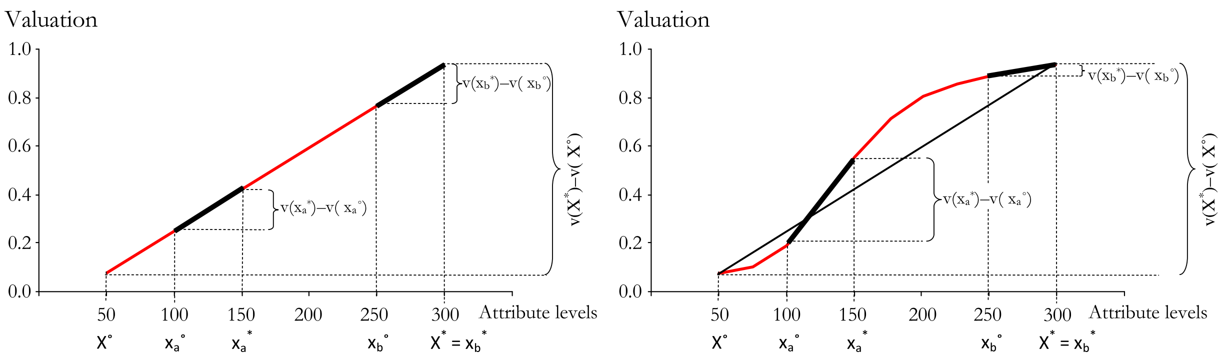


Fig. 1. Different shaped attribute-value functions in the context-specific range of relevant attribute levels for apartment size.



X° = worst attribute level in the global range of attribute levels
X* = best attribute level in the global range of attribute levels

$x_a°$ = worst attribute level in the local range of attribute level (stimulus set *a*)
x_a^* = best attribute level in the local range of attribute level (stimulus set *a*)

$x_b°$ = worst attribute level in the local range of attribute level (stimulus set *b*)
x_b^* = best attribute level in the local range of attribute level (stimulus set *b*)

Fig. 2. Explaining the inconclusive evidence about the relationship between measures of global and local attribute importance (for apartment size (square feet)).

globally: decision makers rely on their attribute-value function to assess the difference in valuation between the best (X^*) and worst (X°) attribute levels in the context—the end-pole attribute levels of decision makers' attribute-value functions – and use that information to answer attribute-importance questions.

If decision makers' attribute-value functions are linear, a positive relationship between local $(v(x_a^*) - v(x_a^\circ))$ and global measures of attribute importance $(v(X^*) - v(X^\circ))$ would exist (see Fig. 2, left panel) – the relative change in valuation is the same irrespective of the range of attribute levels considered. However, empirical evidence about the presumed relationship between measures of global and local importance is inconclusive (Barlas, 2003; Srivastava et al., 1995). We propose that this is caused by a combination of two factors. First, measures of global attribute importance are dependent on a wider range of attribute levels than measures of local attribute importance. Second, both conceptions of attribute importance are generally operationalized with single-point measures that are insensitive to non-linearities in decision makers' attribute-value functions (Tversky & Kahneman, 1991). However, because the range of attribute levels considered is smaller for local than for global attribute-importance measures, single-point measures of local attribute importance are more sensitive to non-linearities in attribute-value functions (e.g., $(v(x_a^*) - v(x_a^\circ)) > (v(x_b^*) - v(x_b^\circ))$ than single-point measures of global attribute importance. The right panel in Fig. 2 shows a hypothetical example of a non-linear relationship between attribute levels and valuation.

Hypothesis 1. The relationship between single-point measures of global attribute importance and single-point measures of local attribute importance is weaker for decision makers with non-linear value functions than for those with linear value functions.

Decision makers, confronted with a choice task, assess the explicit range of attribute levels in the stimulus set, interpret the (local) importance of the attributes involved relying on the attribute-value functions, and make a choice. As single-point measures of global attribute importance are insensitive to non-linearities in the value functions used in the choice task to be able predict decision maker's choices, the predictive accuracy of global measures may be limited. In order to examine this proposition, we compare the predictive accuracy of single-point measures of global attribute importance with that of single-point measures of local attribute importance for decision makers with non-linear and those with linear value functions. If the insensitivity of single-point measures of global attribute importance to non-linearities in attribute-value functions is the main cause for the lack of predictive accuracy, as proposed, we should find no differences in the predictive accuracy of both measures among decision makers with linear attribute-value functions.

Hypothesis 2. The predictive accuracy of single-point measures of global attribute importance is lower than that of single-point measures of local attribute importance, but only for decision makers with non-linear as opposed to linear value functions.

Attribute-value functions as global interpretations of attribute importance

To validate the proposition to operationalize the global interpretation of attribute importance as a decision maker's attribute-value function, we examine the relationship between single-point measures of global attribute importance and the overall shape of attribute-value functions and their properties (e.g., steepness of slope, loss aversion, and diminishing sensitivity). With the importance of relevant personal goals latently influencing both single-point measures of global attribute importance (Van Harreveld & Van der Pligt, 2004) and the construction of attribute-value functions (Tversky & Kahneman, 1991), we expect that single-point measures of global attribute importance relate to the linear and non-linear properties of decision maker's value functions.

First, as the valuation of a change in attribute levels is proposed to be larger for attributes that help achieve more important personal goals (cf., Batra et al., 2001; Fischer, Damodaran, Laskey, & Lincoln, 1987), we propose a relationship between single-point measures of global attribute importance and the steepness of the overall slope of the attribute-value function (Ebenbach & Moore, 2000; Fischer, 1995).

Hypothesis 3a. Single-point measures of global attribute importance positively relate to the steepness of the slope of decision makers' value functions.

Losing an item is more painful than gaining the exact same item is pleasurable: the ratio of the steepness of the slopes of the value function in the loss and gain domain is significantly larger than one (i.e., loss aversion) (Tversky & Kahneman, 1991). What remains unclear, however, is whether this ratio of the steepness of the slopes in the loss and gain domain (i.e., the magnitude of loss aversion) depends on the importance of the relevant personal goals involved for decision makers with S-shaped value functions. Research has shown that the ratio of losses and gains varies across attributes (Dhar & Wertenbroch, 2000; Heath et al., 2000; Klapper, Ebling, & Temme, 2005), possibly due to differences in the importance of the relevant personal goals involved (Tversky & Kahneman, 1991). For example, Carmon and Ariely (2000) find a higher loss aversion for the selling price of tickets for more important basketball games. This suggests that a positive relationship between the single-point measures of global attribute importance and loss aversion exists; the positive relationship between single-point measures of global attribute importance and the steepness of the slope of decision makers' value functions (Hypothesis 3a) is larger in the loss domain than in the gain domain.

Hypothesis 3b. Single-point measures of global attribute importance positively relate to the ratio of the steepness of the slopes in the loss and gain domain for decision makers with S-shaped value functions.

Building on insights from microeconomics on the product specificity of diminishing marginal utilities (Samuelson & Nordhaus, 2001), we hypothesize that there is a relationship between the single-point measure of global attribute importance and the rate of the diminishing marginal valuation of attribute-value functions. The decline in the marginal valuation for each additional unit of improvement of an attribute is hypothesized to be smaller for attributes that help achieve more important personal goals than for attributes that help achieve less important personal goals (Greene & Baron, 2001).

Hypothesis 4. Single-point measures of global attribute importance negatively relate to the rate of diminishing marginal valuation of decision makers' value functions.

Besides the hypothesized relationships between single-point measures of global attribute importance and the properties of attribute-value functions, we also propose that the overall shape of attribute-value functions (concave, S-shaped, convex) depends on the importance of the personal goal the attribute can help to achieve. We hypothesize that single-point measures of global attribute importance are highest among decision makers with a complete convex value function for the attribute, lowest among decision makers with a complete concave value function for the attribute, and intermediate among those with an S-shaped value function. The rationale for this hypothesis relates to the tendency of decision makers to evaluate attribute levels as gains or losses relative to a reference point (i.e., reference dependence). Decision makers' reference points are generally determined by the attribute levels encountered in the products they are accustomed to (Bell & Bucklin, 1999; Helson, 1964). Decision makers are more likely to purchase products that perform more favorable on an attribute that helps them achieve more important personal goals. Hence, they develop a more "extreme" reference point for attributes that help them achieve more important personal goals – a reference point that equals an attribute level at the more favorable end-pole of the relevant range of attribute levels (Bell & Lattin, 2000; Garbarino & Slonim, 2003). For instance, if the fuel efficiency of a car is important to an individual because s/he has strong environmental goals, s/he will buy a car with a relative high mpg-score and use it as a reference point to evaluate the fuel efficiency of other cars. Consequently, other relevant attribute levels are more likely to be perceived as losses (Highhouse & Johnson, 1996; Kristensen & Garling, 1997; Kuhberger, 1998), as a result of which the value function, due to a diminishing sensitivity, takes on a convex shape (see Fig. 2). For attributes that help decision makers achieve less important personal goals, the exact opposite is true. The decision maker will be willing to sacrifice performance on that attribute for attributes that help achieve more important personal goals (Rajendran & Tellis, 1994). As a result of this behavior, the decision maker develops a reference point closer to the less favorable end-pole of the relevant range of attribute levels (Bell & Lattin, 2000). Consequently, other attribute levels will be perceived as gains, resulting in a function that takes on a concave shape due to a diminishing sensitivity (Tversky & Kahneman, 1991) (see Fig. 2). Decision makers for whom the attribute helps achieve moderately important personal goals are expected to develop reference points towards the average or median of the relevant range of attribute levels. Thus, they experience both gains and losses, which, as a result of loss aversion and diminishing sensitivity, results in an asymmetric S-shaped value function, concave for gains and convex for losses.

Hypothesis 5. The global attribute importance is larger for decision makers with convex value functions than for decision makers with concave value functions, and are intermediate for decision makers with S-shaped value functions.

If the above hypotheses cannot be rejected, it can be concluded that operationalizing the global interpretation of attribute importance as a decision maker's attribute-value function provides unique insights into the relationship between global and local attribute-importance measures.

Study 1: renting apartments

To test the hypotheses, we conducted an empirical lab study, involving 189 participants at a large US university. Two-thirds of the participants were male (67.0%) and the participants were on average 21.1 years of age.

Method

As rental apartments represent a relevant product category for the study participants, we chose to use them to test the hypotheses (Potter & Beach, 1994). Furthermore, we decided to test the hypotheses for two attributes related to apartments: monthly rent and size (square feet). In this research, rental apartments refer to single-room, on-campus housing facilities. With few exceptions (2.6%), all participants were apartment renters.

Global importance of attributes

We assessed the global importance of attributes using the well-known direct-rating method. Participants were asked to rate the importance of monthly rent and apartment size on a 9-point scale with the end-poles labeled "not important" – "important". To ensure that these measures were dependent on the implicit range of attribute levels and not on an explicit range of attribute levels (Fischer, 1995), we measured them prior to exposing the participants to any specific attribute levels.

Local importance of attributes

The local importance of both attributes was assessed for a rent of \$150 vs. \$750 and an apartment size of 50 sq. ft. vs. 250 sq. ft. We used decision makers' value functions for both attributes (see hereafter) to estimate the valuations associated with the attribute levels. The difference in valuations associated with these attribute levels was used as a measure for the local importance of both attributes $\left(v(x_{rent}^{\$150}) - v(x_{rent}^{\$750}), v(x_{size}^{250sf}) - v(x_{size}^{50sf})\right)$ (Fischer, 1995).

The shape and the properties of attribute-value functions

We used the direct-rating method to gather data that allowed us to determine the shape and the properties of participants' attribute-value functions for both attributes. Participants rated their valuation of the context-specific range of relevant attribute levels for one attribute at the time (Pennings & Smidts, 2003; Price et al., 2001). The context-specific range of relevant attribute levels was established based on the results of a pre-study involving a different group of 80 participants from the same subject pool. The pre-study revealed that the average rent on campus is about \$500. The average apartment size is 135 sq. ft. The upper and lower bounds for monthly rent were set at \$75 (X_{rent}°) and \$900 (X_{rent}^{*}). For apartment size, these bounds were set at 25 (X_{size}^{*}) and 300 sq. ft. (X_{size}°). The *lower* bounds were set at levels that allowed us to obtain valuation scores for attribute levels close to zero without asking participants to think about apartments with a rent of less than \$75 and a size smaller than the size of a bed. The *upper* bounds were set such that less than 5% of the participants in the pre-study paid more or rented a larger apartment. For both attributes, we set 10 intermediate levels of \$75 and 25-square-foot increments respectively. Participants thus rated 12 attribute levels for each attribute, which is sufficient to determine the overall shape of attribute-value functions. For monthly rent, we asked participants to rate their valuation of apartments with 12 different monthly rent levels on a 100-point scale with the end-poles labeled "I do not appreciate it" – "I highly appreciate it" (Swanson, 1974). We used the word "appreciation" as "valuation" reminded participants too much of the financial value. Similarly, participants were asked to rate their valuation of apartments with 12 different apartment sizes. The attribute levels were presented in a randomized order.

Predictive accuracy

Choice data were collected to study the predictive accuracy of single-point measures of global attribute importance. Participants were asked which apartment they would rent (assuming they were looking for an apartment): apartment a) a 50 sq. ft. apartment for \$150 per month, or apartment b) a 250 sq. ft. apartment for \$750 per month.

To test the rationale for Hypothesis 5, next, participants' reference points for monthly rent and apartment size were determined by asking them to indicate what the monthly rent (\$) and the size (sq. ft.) of their current apartment is (Grewal, Monroe, & Krishnan, 1998; Lichtenstein & Bearden, 1989). Finally, we established the participants' gender (0 = female, 1 = male) and age.

Analyses

Global importance of attributes

The global importance of monthly rent and apartment size is established based on the participants' direct ratings of the importance of both attributes (1 = not important, 9 = important). The participants attach more importance to monthly rent than to apartment size (7.8 vs. 6.4; $t(180) = 9.07$, $p < .05$).

Recall that we assume that methods that merely present information about the context stimulate decision makers to interpret attribute importance globally by assessing the difference in valuation between the best (X^{*}) and worst (X°) attribute levels in the context, and use that information to respond to attribute-importance questions. To test this assumption, we estimated the difference in valuation between the best and worst attribute levels in the context, the end-pole levels of decision makers' estimated value functions ($v(X_{rent}^{\$75}) - v(X_{rent}^{\$900}), v(X_{size}^{300sf}) - v(X_{size}^{25sf})$), and compared these difference scores to the direct-rating measures of global attribute importance. First, in line with the direct-rating scores, we find that participants attach significantly more importance to monthly rent than to apartment size (.69 vs. .55; $t(180) = 2.81$, $p < .05$). Second, we find a significant positive relationship between the direct-rating measures of global attribute importance and the difference in valuation between the best and worst attribute levels of the global range of attribute levels that make up participants' attribute-value function $v(X^{*}) - v(X^{\circ})$, both for monthly rent ($r = .57$, $p < .01$) and for apartment size ($r = .48$, $p < .01$). This suggests that decision makers rely on the implicit range of relevant attribute levels that spans their value function in responding to single-point attribute-importance questions that measure the global importance of attributes.

Local importance of attributes

The local importance of both attributes in the stimulus set involving a rent of \$150 vs. \$750 and an apartment size of 50 sq. ft. vs. 250 sq. ft. was calculated as the difference in estimated valuation associated with these levels ($v(x^{*}) - v(x^{\circ})$). We find that the local importance of rent equals that of apartment size (.47 vs. .46; $t(180) = .39$, $p > .10$).

Consistent with earlier findings (Barlas, 2003; Srivastava et al., 1995) and what motivated this research, we find that the single-point measures of global and local attribute importance do not converge. The global importance measures suggest that participants attach more importance to monthly rent than to apartment size, while the single-point measures of local attribute importance suggest that both attributes are considered equally important. As discussed, we propose that this is caused by the insensitivity of single-point measures of global attribute importance to non-linearities in attribute-value functions.

The shape and the properties of attribute-value functions

We use the rescaled direct-rating data (12 data points per attribute) to establish the shape and the properties of the value functions of monthly rent and apartment size for each individual decision maker. We estimate the overall shape of the value functions using the EXP-IPT technique (e.g., Pennings & Smidts, 2003). The EXP-IPT technique fits the attribute-level valuations

Table 1
Study 1: Results of estimating the best-fitting attribute-value function per individual based on the EXP (Eq. (1a)) and the IPT function (Eq. (1b)).

	Monthly rent attribute									Apartment size attribute								
	Concave (gains) $n = 38$ (20.1%)			S-shape (gains/ losses) $n = 101$ (53.4%)			Convex (losses) $n = 35$ (18.5%)			Concave (gains) $n = 66$ (34.9%)			S-shape (gains/losses) $n = 94$ (49.7%)			Convex (losses) $n = 21$ (11.1%)		
	a	*b*	*c*	α	β	κ	*a*	*b*	*c*	*a*	*b*	*c*	α	β	κ	*a*	*b*	*c*
Parameter[a]																		
Mean	1.243	−.858	−.002	7.939	−.778	.138	−.050	.839	.001	2.419	−2.422	.006	−7.440	3.475	.615	−2.212	2.233	−.002
Median	.919	−.756	−.002	4.762	−.028	.001	−.199	1.326	.001	1.261	−1.380	.004	−5.423	.178	.017	−.659	.827	−.001
Fit indices[b,c]																		
Mean MSE	.079			.055			.057			.048			.057			.061		
Median MSE	.054			.048			.050			.042			.049			.058		
Mean R^2	.771			.923			.864			.917			.919			.903		
Median R^2	.905			.962			.947			.957			.960			.925		

[a] The parameters are estimated with the non-linear least-squares routine ZXMIN from the International Mathematics and Statistics (IMSL) library that employs Fletcher's Quasi–Newton Method. The optimization in this method is performed by searching iteratively for the minimum of an optimization parameter that employs Fletcher's Quasi–Newton Method for minimizing functions of many variables (Dennis & Schnabel, 1983; Gill & Leonard, 2001).
[b] MSE = Mean Squared Error (predicted vs. observed certainty equivalents, scale on a 0–1 scale).
[c] R^2 is calculated by squaring the Pearson correlation between the actual values and the values predicted from the model.

for each decision maker to both the negative exponential function (EXP) (Eq. (1a)) and the log of the inverse power transformation function (IPT) (Eq. (1b)). The former function is either fully concave or fully convex throughout the entire value function. The latter function is flexible with respect to the point of inflexion and the degree of symmetry, given a specific inflexion point (Meade & Islam, 1995), and it is S-shaped.

$$\text{EXP}: \quad V_i(k) = a + b\text{EXP}(-ck) \tag{1a}$$

$$\text{IPT}: \quad V_i(k) = \frac{1}{1 + \text{EXP}[-\alpha - \beta(k/\kappa)\log(1 + \kappa k)]} \tag{1b}$$

Based on a pairwise comparison of the Mean Squared Error (MSE), participants' value functions were classified as either concave/convex or as S-shaped. We find that the overall shape of attribute-value functions differs substantially among decision makers. For monthly rent, we find that 20.1% of the participants exhibit a concave value function, 53.4% reveal an S-shaped value function, and 18.5% display a convex value function. For apartment size, we find that 34.9% of the participants exhibit a concave value function, 49.7% reveal an S-shaped value function, and 11.1% display a convex value function. Table 1 shows the path estimates and model-fit statistics. For the remaining participants, linearity tends to best represent their value functions (7.9% for rent, 4.2% for apartment size). Note that the value functions for monthly rent are downward sloping – monthly rent on the *x*-axis is increasing from the origin, while those for apartment size are sloping upward.

The first property of attribute-value functions examined here is the steepness of the slopes in the loss and gain domains respectively.[2] In line with the reference-dependent theory, we find that the average slope of the attribute-value function is steeper in the loss domain than in the gain domain (see Table 2). The average ratio of both slopes (i.e., loss aversion) is 2.92 for monthly rent and 2.06 for apartment size.

The rate of diminishing marginal valuation[3] was not significantly different between the gain and loss domain, neither for the attribute monthly rent (.67 vs. .70; $F(1,161) = .57$, $p > .10$) nor for apartment size (.67 vs. .72; $F(1,168) = 2.46$, $p > .10$). Hence, for a decision maker with an S-shaped value function, we used the average across both domains as a measure for the rate of diminishing marginal valuation concerning an attribute. The average rate of diminishing marginal valuation is .71 for monthly rent and .74 for apartment size (see Table 2). Note that an *increase* in the calculated rate reflects a *decrease* in diminishing marginal valuation. We rescaled the rate (*1-rate*) such that an *increase* in the calculated rate reflects an *increase* in diminishing marginal valuation.

Results

Consistent with Hypothesis 1, we find a significant smaller (and even insignificant) correlation between the single-point measures of the global and the local importance of rent for decision makers with a non-linear value function than for those with a linear value function ($r = .04$, $p = .33 < r = .49$, $p < .05$; $z = 1.66$, $p < .05$). The same is found for apartment size ($r = .03$, $p = .41 < r = .54$, $p < .10$; $z = 1.27$, $p = .10$). In line with Hypothesis 2, we further find that the predictive accuracy of single-point measures of global attribute importance is smaller than that of local attribute-importance measures for participants with non-linear valuations (47.8% vs. 65.4%; $z = 2.79$, $p < .05$). No significant differences are found for participants with linear value functions (62.5% vs. 75.0%; $z = 1.00$, $p > .10$). These results suggest that single-point measures of global attribute importance are more insensitive to non-linearities in the value functions than local attribute-importance measures.

Global attribute importance and the properties of attribute-value functions

We next examine the relationship between single-point measures of global attribute importance and the properties and overall shape of decision makers' attribute-value functions. In testing the relationship between single-point measures of global attribute

[2] For participants with a fully concave or convex value function for an attribute, the steepness of the slope is calculated based on the first derivative of Eq. (1a) using the rescaled data. For those participants with an S-shape value function, we employ the two-piece value function technique (e.g., EXP-IPT technique, e.g., Pennings & Smidts, 2003). Accordingly, we divide their value function into two domains – the domain above the reference point (cf., gains) and the domain below the reference point (cf., losses), and estimate the EXP function (Eq. (1a) separately for both domains. Next, we calculate the steepness of the estimated value function in both the gain and loss domain, based on the first derivative of Eq. (1a), using the rescaled data. In addition, we establish the ratio of the steepness of the slopes in the loss and gain domain for those with an S-shaped value function.

[3] We establish the *rate of diminishing marginal valuation* for an attribute by taking the second derivative of Eq. (1a), calculate the relative change in valuation for each pair of independent attribute levels, and determine the average rate of diminishing marginal valuation using the rescaled data. This is done for participants with fully concave and convex value functions. For participants with an S-shaped value function, we use the same technique to calculate the rate of diminishing marginal valuation in the gain and loss domain.

Table 2
Study 1: Properties of decision makers' attribute-value functions.

	Steepness of slopes[a]				Ratio of steepness of slopes in loss/gain domain[b]		Rate of diminishing marginal valuation[c]	
	Monthly rent		Apartment size		Monthly rent	Apartment size	Monthly rent	Apartment size
	Loss (n = 136)	Gain (n = 139)	Loss (n = 115)	Gain (n = 160)	(n = 101)	(n = 94)	(n = 174)	(n = 181)
Average (St. dev.)	.0071 (.0636)	.0025 (.0156)	.0111 (.0416)	.0052 (.0126)	2.92 (4.03)	2.06 (2.54)	.71 (.23)	.74 (.23)
Median	.0010	.0007	.0042	.0028	1.48	1.28	.76	.78
Percentiles								
20th	.0035	.0028	.0014	.0003	.20	.27	.49	.49
40th	.0013	.0012	.0032	.0019	1.10	1.01	.69	.75
60th	.0008	.0005	.0053	.0039	2.01	1.56	.82	.86
80th	.0006	.0001	.0091	.0053	4.63	3.41	.94	.94

[a] The slope steepness in the loss (gain) domain is calculated across decision makers with convex, concave and S-shaped functions.
[b] The ratio of steepness of slopes in loss/gain domain is calculated for decision makers with an S-shaped value function.
[c] The rate of diminishing marginal valuation is calculated across decision makers with concave, S-shaped, and convex functions.

Table 3
Study 1: Predictive accuracy of attribute-value functions.

	Percentage of actual product choices correctly predicted (hit rate)	Percentage of improvement over random model[a]	Log likelihood of logistic model
Individual level (based on the maximum utility)	71.3	42.6	
Aggregate level (based on logistics regression)	72.1	44.2	150.996

Note that the dependent variable is decision makers' choice between *apartment (a)* a 50 sq. ft. apartment for \$150 per month or *apartment (b)* a 250 sq. ft. apartment for \$750 per month. The independent variables are decision makers' valuations associated with the different attribute levels in the choice set.
[a] Percentage improvement over random model = [(percent correctly predicted by the approach − percent correctly predicted by random model)/(100 − percent correctly predicted by random model)] × 100 (Srinivasan, 1988).

importance and the steepness and diminishing marginal valuation, we account for the effect of the shape of value functions by including dummies for the shape of the value function as covariates in the correlation analyses. Single-point measures of global attribute importance positively relate to the steepness of the slopes of the value function, both for monthly rent (r_{rent} = .18, p < .01) and apartment size (r_{size} = .13, p < .05), supporting Hypothesis 3a.

In accordance with Hypothesis 3b, a significant relationship is found between single-point measures of global attribute importance and loss aversion, both for monthly rent (r_{rent} = .19, p < .05) and apartment size (r_{size} = .17, p < .05). The ratio between losses and gains is larger for attributes that are more important to decision makers.

Consistent with Hypothesis 4, we find that the rate of the diminishing marginal valuation decreases with an increase in the global importance of monthly rent (r_{rent} = −.19, p < .05). A similar relationship is found for apartment size (r_{size} = −.18, p < .05). The decline in the marginal valuation for each additional unit of improvement of an attribute reduces with the global importance of attributes.

Global attribute importance and the overall shape of attribute-value functions

Consistent with Hypothesis 5, we find that the importance of an attribute is highest (lowest) among participants with a convex (concave) value function for the attribute (see Fig. 3). Participants with an S-shaped value function rate the importance of attributes in between the attribute-importance ratings of participants who exhibit a convex and concave value function, for both monthly rent ($F(2,158) = 4.73$, p < .01) and apartment size ($F(2,160) = 3.36$, p < .05). In line with the rationale for these results, mediation analyses confirmed that the relationship between the global importance of attributes and the overall shape of attribute-value functions is mediated by participants' reference points.

Predictive accuracy of attribute-value functions

The global interpretation considers attribute importance to be a stable characteristic that does not depend on a particular stimulus set, provided that the stimuli do not disturb the person's implicit contextual assumption. This implies that attribute-value functions can be used to predict decision makers' preferences (Heath et al., 1999). We explicitly tested this by exploring the predictive accuracy of attribute-value functions in more detail by using the value functions to estimate the valuation of the attribute levels associated with the two apartments participants choose from in the choice task described before. Next, we calculated the individual hit rate – the percentage of times attribute-value functions correctly predict each individual's choice – using the maximum utility rule (Srinivasan & Park, 1997). This rule predicts that each individual chooses the alternative in the choice set with the highest predicted utility (based on the sum of the valuations associated with the relevant attribute levels, predicted based on the estimated attribute-value functions). In addition, using logistic regressions, we examine the aggregate hit rate by comparing the predicted

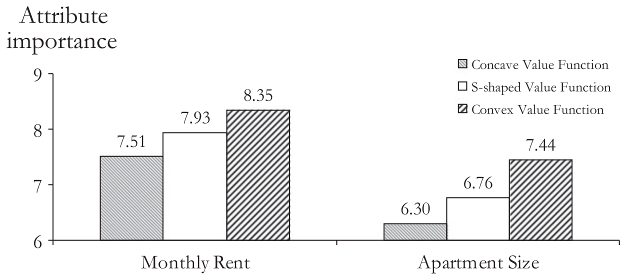


Fig. 3. The relationship between the global importance of attributes and the overall shape of attribute-value functions in the context-specific range of relevant attribute levels for monthly rent and apartment size.

Table 4
Study 2: Methods used to measure the global and local importance of attributes.

	Description	Scale
Global importance		
G_1 direct-rating I	Individuals rate each attributes on a scale	1 = not important, 9 = very important
G_2 direct-rating II	Individuals rate each attributes on a scale	Magnitude scale, 10 cm line, end poles not important and very important
G_3 direct-ranking	Individuals rank the attributes in order of importance	
G_4 relative-rating	Individuals rate the importance of attributes relative to each other	−5 = attribute 1 is most important, +5 = attribute 2 is most important
G_5 point allocation	Individuals distribute 100 points among the attributes (important attributes received more points)	
Local importance		
L_1 direct-rating I	Individuals rate the importance of the difference between two attribute levels	1 = not important, 9 = very important
L_2 direct-rating II	Individuals rate how important an attribute was in choice	1 = not important, 9 = very important
L_3 difference score	The difference in estimated valuations associated with two attribute levels (estimated based on the attribute-value functions)	
L_4 swing-weight	Individuals indicate which attribute they would upgrade first if they were confronted with a product that has attributes with only the worst possible levels available. This attribute receives 100 points, and next individuals are asked to upgrade a second attribute, and indicate how many points this attribute would receive (Von Winterfeldt & Edwards, 1986)	
L_5 trade-off	Individuals conduct a matching task – for instance, adjust one attribute of one product, such that the product becomes equally attractive to the other product that is fully described on all available attributes, from which attribute importance is derived (Keeney & Raiffa, 1976)	

Table 5
Study 2: Global and local importance of price and hard-drive size.

	Importance (price vs. size of hard drive)		Conclusions
Global importance			
G_1	7.7 vs. 6.7; $F(1,191) = 35.3$, $p < .01$		The global importance of the price is consistently higher than that of the size of the hard drive
G_2	8.1 vs. 6.9; $F(1,191) = 47.1$, $p < .01$		
G_3	74% vs. 26%; $\chi^2 = 44.1$, $p < .01$		
G_4	−1.4 vs. 0; $t(191) = -9.1$, $p < .01$		
G_5	59.2 vs. 40.8; $F(1,191) = 67.8$, $p < .01$		
	Stimulus set 1: \$500, 80 GB \$1000, 240 GB	Stimulus set 2: \$1500, 400 GB \$2000, 560 GB	
Choice (%)	15.6% vs. 84.4%, $\chi^2 = 90.8$, $p < .01$	87.4% vs. 12.6%, $\chi^2 = 107.1$, $p < .01$	
Local importance			
L_1	6.5 vs. 7.3; $F(1,190) = 12.4$, $p < .01$	7.1 vs. 4.0; $F(1,190) = 118.3$, $p < .01$	The local importance of the price and size depends on the stimulus set
L_2	6.4 vs. 7.0; $F(1,190) = 9.2$, $p < .01$	7.7 vs. 5.6; $F(1,190) = 61.4$, $p < .01$	
L_3	0.12 vs. 0.20; $F(1,190) = 38.5$, $p < .01$	0.16 vs. 0.11; $F(1,190) = 13.5$, $p < .01$	
L_4	76.4 vs. 84.3; $F(1,190) = 5.9$, $p < .05$	88.5 vs. 49.5; $F(1,190) = 13.4$, $p < .01$	
L_5	1.02 vs. 2.0; $F(1,190) = 30.8$, $p < .01$	0.16 vs. .40; $F(1,190) = 422.9$, $p < .01$	

choice share – the percentage of respondents predicted to choose each alternative based on the value associated with the attribute levels of the two alternatives in the choice set – with the actual choice share, the actual percentage of individuals choosing each alternative.

Table 3 shows that the predictive accuracy of attribute-value functions is substantial, both at the individual level (71.3% accuracy) and the aggregate level (72.1% accuracy). Both hit rates represent a significant improvement over the random model.

The results of Study 1 suggest that decision maker's attribute-value functions may be a valid representation of decision-maker's global interpretation of attribute importance. While Study 1 provides support for the hypotheses, Study 1 is limited in the number of attribute-importance measures examined. To address this, a second study is conducted that measures the importance of attributes in a different context for two attribute ranges using ten different methods.

Study 2: purchasing a computer

The second empirical lab study involved 192 participants at a large US university. Two-thirds of the participants were male (63.0%) and the participants were on average 20.7 years of age.

Method

In Study 2, we test the hypotheses in the context of computers, focusing on price (\$) and the size of the hard drive (GB), two attributes a pre-study among a different group of 64 participants from the same subject pool revealed are deemed important when purchasing a computer. All participants owned a computer.

Global importance of attributes

We assessed the global importance of attributes using: (G_1) direct-rating method I, (G_2) direct-rating method II, (G_3) direct-ranking method, (G_4) relative-rating method, and (G_5) point-allocation method. Table 4 provides details. The global attribute importance is measured prior to the participants' being exposed to the levels of the attributes studied (Fischer, 1995). The five methods were administered in a randomized order. No order effects were found.

Local importance of attributes

The local importance of price and size of the hard drive were measured for two stimulus sets: (1) \$500, 80 GB vs. \$1000, 240 Gb, (2) \$1500, 400 GB vs. \$2000, 560 Gb. For each set, participants were asked to decide which computer they would purchase (these data will also be used to study the accuracy of single-point measures of global attribute importance). Subsequently, the local importance of both attributes was measured using: (L_1) direct-rating method I, (L_2) direct-rating method II, (L_3) difference in estimated valuations (see Study 1), (L_4) swing-weight method (Von Winterfeldt & Edwards, 1986), and (L_5) trade-off method (Keeney & Raiffa, 1976). Please consult Table 4 for method details. The order was randomized and no order effects were found. Also, the order in which the two stimulus sets were offered was randomized. As no order effects were found, all analyses will be conducted across both stimulus sets including a dummy variable to account for each stimulus set.

The shape and the properties of attribute-value functions

The shape and the properties of participants' attribute-value functions for both attributes were determined as described in Study 1. The context-specific range of relevant attribute levels was established based on the results of a pre-study involving a different group of 64 participants from the same subject pool.

The upper and lower bounds for price were set at \$250 (X°_{price}) and \$2250 (X^{*}_{price}). For the size of the hard drive, these bounds were set at 1 (X^{ast}_{size}) and 640 GB (X°_{size}). For both attributes, we set eight intermediate levels of \$250 and 80 GB increments respectively. Participants thus rated nine attribute levels for each attribute on a 100-point scale with the end-poles labeled "I really dislike it" – "I really like it". The attribute levels were presented in a randomized order.

Next, the participants' reference points for price and hard-drive size were determined by asking them to indicate the price (\$) and hard-drive size (GB) of the computer they currently own. Finally, we established the participants' gender (0 = female, 1 = male) and age.

Analyses

Global and local importance of attributes

Table 5 shows that all five global importance measures indicate that participants attach more importance to the price of the computer than the size of the hard drive. As in Study 1, we find significant positive relationships between the direct-rating measures of global attribute importance (G_1–G_5) and the difference in valuation between the best and worst attribute levels of the global range of attribute levels that make up participants' attribute-value function $v(X^{*}) - v(X^{\circ})$, both for price (r_{range} = .53–.76) and for the size of the hard drive (r_{range} = .56–.82).

The local importance of both attributes is shown to depend on the stimulus set. When deciding between a \$500, 80 GB computer and a \$1000, 240 GB computer, size of the hard drive is more important than price. However, this reverses when deciding

Table 6
Study 2: Results of estimating the best-fitting attribute-value function per individual based on the EXP (Eq. (1a)) and the IPT function (Eq. (1b)).

	Price attribute									Size of hard drive attribute								
	Concave (gains) n = 27 (14.1%)			S-shape (gains/losses) n = 85 (44.3%)			Convex (losses) n = 64 (33.3%)			Concave (gains) n = 88 (45.8%)			S-shape (gains/losses) n = 72 (37.5%)			Convex (losses) n = 20 (10.4%)		
	a	b	c	α	β	κ	a	b	c	a	b	c	α	β	κ	a	b	c
Parameter[a]																		
Mean	2.332	−1.327	−1.662	2.257	−7.772	−.270	−.106	1.114	5.197	.953	−.954	6.414	−2.854	16.379	.891	−3.163	3.144	−1.021
Median	1.434	−.332	−1.345	2.177	−6.455	−.697	−.004	.992	2.821	.969	−.944	4.472	−2.626	13.453	.217	−.772	.735	−.943
Fit indices[b,c]																		
Mean MSE	.006			.003			.009			.004			.047			.014		
Median MSE	.003			.003			.007			.003			.046			.011		
Mean R^2	.945			.950			.924			.961			.966			.916		
Median R^2	.967			.962			.937			.965			.974			.907		

[a] The parameters are estimated with the non-linear least-squares routine ZXMIN from the International Mathematics and Statistics (IMSL) library that employs Fletcher's Quasi-Newton Method. The optimization in this method is performed by searching iteratively for the minimum of an optimization parameter that employs Fletcher's Quasi-Newton Method for minimizing functions of many variables (Dennis & Schnabel, 1983; Gill & Leonard, 2001).
[b] MSE = Mean Squared Error (predicted vs. observed certainty equivalents, scale on a 0–1 scale).
[c] R^2 is calculated by squaring the Pearson correlation between the actual values and the values predicted from the model.

Table 7
Study 2: Properties of decision makers' attribute-value functions.

	Steepness of slopes[a]				Ratio of steepness of slopes in loss/gain domain[b]		Rate of diminishing marginal valuation[c]	
	Price		Size of hard drive		Price	Size of hard drive	Price	Size of hard drive
	Loss (n = 149)	Gain (n = 112)	Loss (n = 92)	Gain (n = 160)	(n = 85)	(n = 72)	(n = 176)	(n = 180)
Average (St.dev.)	.0070 (.0254)	.0042 (.0099)	.0080 (.0107)	.0057 (.0036)	2.45 (2.93)	1.96 (1.70)	.65 (.19)	.76 (.21)
Median	.0014	.0010	.0061	.0053	1.58	1.57	.65	.75
Percentiles								
20th	.0057	.0030	.0017	.0032	.40	.60	.47	.48
40th	.0021	.0016	.0046	.0045	1.13	1.29	.61	.69
60th	.0011	.0009	.0065	.0059	1.95	1.80	.71	.82
80th	.0006	.0005	.0115	.0072	3.90	2.89	.86	.92

[a] The steepness of slopes in the loss (gain) domain is calculated across decision makers with convex (concave) and S-shaped value functions.
[b] The ratio of steepness of slopes in loss/gain domain is calculated for decision makers with an S-shaped value function.
[c] The rate of diminishing marginal valuation is calculated across decision makers with concave, S-shaped, and convex value functions.

Table 8
Study 2: Correlations between global and local attribute-importance measures for decision makers with linear vs. non-linear value functions.

Methods	Linear value function					Non-linear value function				
	G_1	G_2	G_3	G_4	G_5	G_1	G_2	G_3	G_4	G_5
Price										
L_1	$.50^{**}$	$.47^{**}$	$.50^{**}$	$.42^{**}$	$.51^{**}$	$.09^{ns}$	$.13^{*}$	$.08^{ns}$	$.12^{*}$	$.09^{ns}$
L_2	$.56^{**}$	$.51^{**}$	$.43^{**}$	$.32^{*}$	$.32^{**}$	$.10^{*}$	$.18^{*}$	$.16^{**}$	$.20^{**}$	$.17^{**}$
L_3	$.38^{*}$	$.42^{**}$	$.43^{**}$	$.34^{*}$	$.35^{**}$	$.01^{ns}$	$.01^{ns}$	$.03^{ns}$	$.01^{ns}$	$.05^{ns}$
L_4	$.45^{**}$	$.43^{**}$	$.20^{ns}$	$.29^{*}$	$.30^{**}$	$.09^{ns}$	$.11^{*}$	$.15^{**}$	$.15^{**}$	$.15^{**}$
L_5	$.31^{*}$	$.41^{**}$	$.19^{ns}$	$.23^{*}$	$.34^{**}$	$.00^{ns}$	$.07^{ns}$	$.11^{*}$	$.14^{**}$	$.12^{**}$
	$.44^{**}$	$.45^{**}$	$.35^{**}$	$.32^{**}$	$.36^{**}$	$.06^{ns}$	$.10^{*}$	$.11^{*}$	$.12^{*}$	$.12^{**}$
Size										
L_1	$.45^{**}$	$.51^{**}$	$.29^{*}$	$.38^{**}$	$.42^{**}$	$.06^{ns}$	$.10^{ns}$	$.15^{*}$	$.12^{*}$	$.13^{*}$
L_2	$.60^{**}$	$.49^{**}$	$.43^{**}$	$.19^{ns}$	$.35^{**}$	$.08^{ns}$	$.18^{**}$	$.17^{**}$	$.17^{**}$	$.18^{**}$
L_3	$.48^{**}$	$.29^{*}$	$.30^{**}$	$.26^{*}$	$.17^{ns}$	$.04^{ns}$	$.05^{ns}$	$.02^{ns}$	$.03^{ns}$	$.01^{ns}$
L_4	$.49^{**}$	$.44^{**}$	$.24^{*}$	$.27^{*}$	$.36^{**}$	$.12^{*}$	$.05^{ns}$	$.08^{ns}$	$.06^{ns}$	$.17^{**}$
L_5	$.51^{**}$	$.39^{**}$	$.22^{*}$	$.28^{*}$	$.37^{**}$	$.00^{ns}$	$.00^{ns}$	$.01^{ns}$	$.04^{ns}$	$.01^{ns}$
	$.51^{**}$	$.42^{**}$	$.30^{**}$	$.28^{*}$	$.33^{**}$	$.07^{ns}$	$.08^{ns}$	$.10^{**}$	$.08^{ns}$	$.10^{*}$

Note. The correlations are calculated across both stimulus sets studied.
* $p < .05$.
** $p < .01$.

between a $1500, 400 GB computer and a $2000, 560 GB computer. These results again suggest that the single-point measures of global and local attribute-importance measures do not converge.

The shape and the properties of attribute-value functions

We use the direct-rating data (9 data points per attribute) to establish the shape and the properties of the value functions for price and size of the hard drive for each individual decision maker (see Study 1 for details). We find that the overall shape of attribute-value functions differs substantially among decision makers. For price, we find that 14.1% of the participants exhibit a concave value function, 44.3% reveal an S-shaped value function, and 33.3% display a convex value function. For size of the hard drive, we find that 45.8% of the participants exhibit a concave value function, 37.5% reveal an S-shaped value function, and 10.4% display a convex value function. Table 6 shows the path estimates and model-fit statistics. For the remaining participants, linearity tends to best represent their value functions (8.3% for price, 6.3% for size of the hard drive).

In line with the reference-dependent theory, we find that the average slope of the attribute-value function is steeper in the loss domain than in the gain domain (see Table 7). The average ratio of both slopes (i.e., loss aversion) is 2.45 for price and 1.96 for the size of the hard drive. The rate of diminishing marginal valuation was not significantly different between the gain and loss domain, neither for price (.63 vs. .66; $F(1,191) = 1.04$, $p > .10$) nor for size of the hard drive (.74 vs. .76; $F(1,191) = 0.95$, $p > .10$). Hence, for a decision maker with an S-shaped value function, we use the average across both domains as a measure for the rate of diminishing

Table 9
Study 2: Predictive accuracy of global vs. local measures for decision makers with linear vs. non-linear value functions.

Methods	Linear value function (%)	Non-linear value function (%)
G_1	68.1	55.6
G_2	68.5	57.7
G_3	69.5	56.8
G_4	70.5	55.3
G_5	64.8	53.6
	68.3	55.8
L_1	75.9	73.9
L_2	72.9	70.9
L_3	78.5	79.6
L_4	74.5	70.3
L_5	70.3	68.8
	74.4	72.7

To predict decision makers' choices with regards to stimulus set 1: $500, 80 GB vs. $1000, 240 Gb, and stimulus set 2: $1500, 400 GB vs. $2000, 560 Gb, we assume that they choose the computer that scores most favorable on the most important attribute.

Table 10
Study 2: Correlations between global attribute-importance measures and value-function properties.

Methods	Steepness of slopes		Ratio of steepness of slopes in loss/gain domain		Rate of diminishing marginal valuation	
	Price	Size	Price	Size	Price	Size
G_1	.14*	.21**	.26**	.35**	−.11*	−.18**
G_2	.15**	.19**	.24*	.29**	−.12*	−.16*
G_3	.05ns	.17**	.29**	.21*	−.05ns	−.05ns
G_4	.12*	.23**	.27**	.31**	−.07ns	−.13*
G_5	.16**	.21**	.18*	.30**	−.18*	−.14*
	.13**	.24**	.23**	.29**	−.12*	−.11*

Note. The correlations involving the ratio's only include participants with an S-shaped value function. Further, the correlations involving the steepness of slopes include the absolute steepness measures in both the gain and loss domain.
A series of regression models revealed that the value-function properties predict a significant proportion of the variance in global attribute importance (G1–G5).
* $p < .05$.
** $p < .01$.

Table 11
Study 2: The global importance of price and size for participants with different shaped value functions.

Methods	Shape of value function			
	Concave	S-shaped	Convex	F-value/χ^2
Price				
G_1	7.37	7.55	8.08	4.38*
G_2	7.67	7.88	8.62	5.48**
G_3	8.3%	25.2%	30.2%	15.1**
G_4	−.44	−.82	−2.56	17.6**
G_5	51.0	55.9	67.1	16.2**
Size				
G_1	6.34	7.18	7.40	8.7**
G_2	6.32	7.54	7.70	9.3**
G_3	3.3%	7.8%	15.6%	42.4**
G_4	−2.34	−.67	.70	30.0**
G_5	35.3	44.4	56.3	23.1**

Note. Response scales: (G_1 and G_2) 1 = unimportant, 9 = important, (G_3) rank-order (price ranked number 1), (G_4) −5 price is most important, 5 = size is most important, (G_5) 100 point-allocation.
* $p < .05$.
** $p < .01$.

marginal valuation concerning an attribute. The average rate of diminishing marginal valuation is .65 for price and .75 for size of the hard drive (see Table 7).

Results

In line with Hypothesis 1, we find smaller correlations between single-point measures of global and local attribute importance for decision makers with a non-linear value function than for those with a linear value function, both for price ($r = .38$, $p < .01 > r = .10$, $p < .05$; $z = 3.59$, $p < .01$) and size of the hard drive ($r = .37$, $p < .01 > r = .09$, $p = .11$; $z = 3.82$, $p < .01$) (see Table 8 for details).

Consistent with Hypothesis 2, we find that the predictive accuracy of single-point measures of global attribute importance is smaller than that of local attribute-importance measures for participants with non-linear value functions (55.8% vs. 72.7%; $z = 2.59$, $p < .05$). No significant differences are found for participants with linear value functions (68.3% vs. 74.4%; $z = .59$, $p > .10$) (see Table 9). These results are consistent with Study 1 and suggest that decision makers rely on attribute-value functions when responding to attribute-importance questions.

Global attribute importance and the properties of attribute-value functions

In line with Hypothesis 3a, we find that single-point measures of global attribute importance positively relate to the steepness of the slopes of the value functions, both for price ($r_{price} = .13$, $p < .01$) and the size of the hard drive ($r_{size} = .25$, $p < .01$) (see Table 10). The slope of the value functions is steeper for attributes that help achieve more important personal goals.

Consistent with the results of Study 1 and in accordance with Hypothesis 3b, a significant relationship is found between single-point measures of global attribute importance and loss aversion, both for the price ($r_{price} = .23$, $p < .01$) and the size of the hard drive ($r_{size} = .29$, $p < .01$). The ratio between losses and gains is larger for attributes that are more important to decision makers.

Along the lines of Hypothesis 4, we find that with an increase in the global importance of price, the rate of the diminishing marginal valuation decreases ($r_{price} = -.12$, $p < .05$). A similar relationship is found for the size of the hard drive ($r_{size} = -.11$, $p < .05$).

Global attribute importance and the overall shape of attribute-value functions

Consistent with Hypothesis 5, we find that the importance of an attribute is highest (lowest) among participants with a convex (concave) value function for the attribute. Participants with an S-shaped value function rate the importance of attributes in between the attribute-importance ratings of participants who exhibit a convex and concave value function, for both price and the size of the hard drive (see Table 11). Mediation analyses confirmed that that the relationship between the global importance of attributes and

Table 12
Study 2: Predictive accuracy of attribute-value functions.

	Percentage of actual product choices correctly predicted (hit rate)	Percentage of improvement over random model[a]	Log likelihood of logistic model
Stimulus set 1: \$500, 80 GB vs. \$1000, 240 GB			
Individual level (based on the maximum utility)	77.6	55.2	
Aggregate level (based on logistics regression)	73.9	47.8	189.452
Stimulus set 2: \$1500, 240 GB vs. \$2000, 560 GB			
Individual level (based on the maximum utility)	80.2	60.4	
Aggregate level (based on logistics regression)	76.0	52.0	168.954

[a] Percentage improvement over random model = [(percent correctly predicted by the approach − percent correctly predicted by random model)/(100 − percent correctly predicted by random model)] × 100 (Srinivasan, 1988).

the overall shape of attribute-value functions is mediated by participants' reference points.

Predictive accuracy of attribute-value functions

Finally, we examine the predictive accuracy of attribute-value functions in more detail using the value functions to estimate the valuation of the attribute levels associated with the two sets of computers participants were asked to choose from in the choice task described before. Next, we calculated the individual hit rate as well as the aggregate hit rate, as described in Study 1. Table 12 shows the results regarding the predictive accuracy of attribute-value functions. We find that the predictive accuracy of attribute-value functions is substantial for both stimulus sets. Both hit rates represent a significant improvement over the random model.

Discussion

The results of Study 2 corroborate the findings of Study 1 across different attribute-importance measures and a different context. We elaborate in the Main Discussion.

Main discussion

To gain a better understanding about decision maker's interpretations of the global and local importance of attributes and their relationship, we proposed to operationalize the global interpretation of attribute importance as a function – decision makers' attribute-value functions. We empirically examined the validity of this proposition by demonstrating that single-point measures of global attribute importance significantly relate to the shape and properties of attribute-value functions. More specifically, the global importance is larger for decision makers with a convex value function than for decision makers with a concave value function, and intermediate for decision makers with an S-shaped value function. Furthermore, the global importance of attributes positively relates to the (ratio of the) steepness of the slopes and negatively to the rate of diminishing marginal valuation. Second, we demonstrated that the predictive accuracy of attribute-value functions is significantly better than the random model. We conclude that decision makers' idiosyncratic attribute-value functions yield significant insights into the global and local importance of attributes and their relationship.

The importance of understanding the relationship between the global and local measures of attribute importance is critical. Without having an accurate, conceptual understanding of the relationship between global and local measures of attribute importance, doubts about the validity of existing methods for attribute importance measurement will persist. While common (single-point) measures of global attribute importance are useful to determine the relative importance of multiple attributes in a specific context, they provide little guidance in understanding how the global and local importance of attributes are related. Take for instance the results of Study 2. The single-point measures of global importance consistently suggest that price is considered more important that the size of a hard drive in the context of purchasing a computer (i.e., global importance). However, in deciding between a $500, 80 GB and a $1000, 240 GB computer, the size of the hard drive is more important than the price attribute (i.e., local importance). Operationalizing the global importance of attributes as a value function helps explain this apparent inconsistency between the global and local importance of attributes. These insights go beyond the range sensitivity principle and value-comparison hypothesis (Fischer, 1995) that presume a linear relationship between attribute levels and valuation.

Combined with the predictive accuracy, there results suggest great promise for future research on using decision makers' attribute-value functions for measuring the importance of attributes.

Limitations and future research

Because our approach is new, our empirical findings, while clear and unequivocal taken on their own, should be considered suggestive of a future research program addressing decision makers' attribute-value functions as global interpretations of attribute importance in a variety of substantive settings. First, the proposed hypotheses may be tested using other attribute-importance measures and contexts. Second, the findings may be generalized by investigating other products and attributes. This research can for instance be extended to attributes for which decision makers have non-monotonic value functions. More research on the stability and context specificity of decision makers' attribute-value functions is also desirable (Hoeffler & Ariely, 1999). In light of the research findings, it may be valuable to examine if and how the overall shape of attribute-value functions may be altered, such that, for instance, choice behavior may change.

Providing additional evidence for the predictive accuracy is also called for. Besides using attribute-value functions to predict real (vs. stated) choice behavior, the predictive accuracy of the attribute-value functions should also be examined in more complex or difficult choice contexts. Furthermore, research examining the reliability of decision makers' idiosyncratic attribute-value functions is recommended.

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