

# The benefits of global scaling in multi-criteria decision analysis

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## Abstract

When there are multiple competing objectives in a decision-making process, Multi-Attribute Choice scoring models are excellent tools, permitting the incorporation of both subjective and objective attributes. However, their accuracy depends upon the subjective techniques used to construct the attribute scales and their concomitant weights. Conventional techniques using local scales tend to overemphasize small differences in attribute measures, which may yield erroneous conclusions. The Range Sensitivity Principle (RSP) is often invoked to adjust attribute weights when local scales are used. In practice, however, decision makers often do not follow the prescriptions of the Range Sensitivity Principle and under-adjust the weights, resulting in potentially poor decisions. Examples are discussed as is a proposed solution: the use of global scales instead of local scales.

Keywords: decision analysis, multiple criteria analysis, range sensitivity, global scale, local scale, importance weight, swing weight.

## 1 Introduction

Multi-Attribute Choice scoring model techniques such as the Simple Multi-Attribute Review Technique (SMART) and its improvements (SMARTS, SMARTER) (Edwards & Barron, 1994), MAVT, and MAUT are excellent tools for decision making, permitting the incorporation of both objective and subjective attributes into the decision-making process. They typically require the assignment of a weight to each attribute that is thought relevant in conjunction with the development of some corresponding attribute scale. However, their utility depends upon the techniques used both to construct the attribute scales and to determine the proper weights. In Figure 1, several scale choices are shown for an example involving 3 large screen plasma TVs that cost \$5,200, \$5,075, and \$5,050.

The scale choices depicted are: Natural Scale, a Local Scale, and a Global Scale. Definitions are presented below:

**Option set.** The group of data points for the parameter (e.g., price, style, comfort) currently under consideration. In Figure 1, the option set consists of the 3 data points \$5,200, \$5,075, and \$5,050.

**Natural scale.** The unadulterated values of the parameter being measured in their original units (e.g., dollars) showing the full range (all values) of samples

in the option set. In Figure 1 the natural scale ranges from \$5,050 to \$5,200.

**Local scale.** A remapped scale in which the best value from the natural scale has been remapped to 1, 10, or 100 while the worst value from the natural scale has been remapped to 0. In Figure 1, the natural value of \$5,050 has been remapped to 10 on the local scale while the natural value of \$5,200 has been remapped to 0 on the local scale.

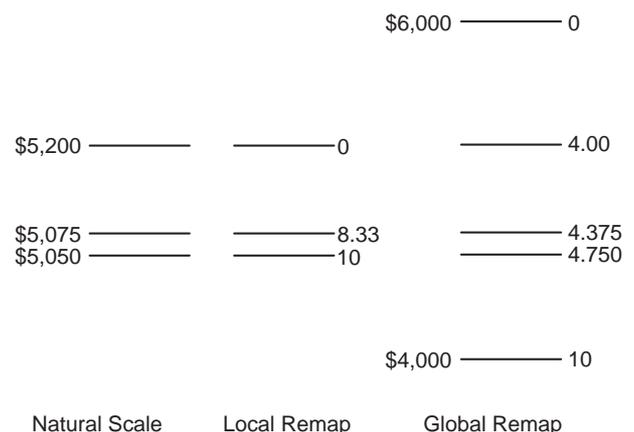


Figure 1: Natural and remapped scales for prices of \$5,050; \$5,075; and \$5,200. For the global remapping the decision-maker established the global extremes as \$6,000 (worthy of a score of 0) and \$4,000 (worthy of a score of 10).

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**Global scale.** A remapped scale in which the best value from the decision-maker's experience, aspirations, or imagination (not the best value from the option set) has been remapped to 1, 10, or 100 while the worst value from the decision-maker's experience, aspirations, or imagination has been remapped to 0. In Figure 1, the natural value of \$4,000 has been remapped to 10 on the global scale while the natural value of \$6,000 has been remapped to 0 on the global scale. In global scaling, the decision-maker must determine the endpoints of the scale, that is what natural value is worthy of a score of 0 and what natural value is worthy of a score of 10. Unlike some definitions, this definition of Global Scale does not include *all* possible values of the parameter but only the range bounded by extremes corresponding to the decision-maker's perception of values of 0 and 10. Intermediate values are interpolated.

**Global extremes.** The natural values corresponding to the global scale extremes. In Figure 1 the Global Extremes are \$4,000 and \$6,000.

**Multiattribute value function.** A mathematical expression that combines attribute ratings from 2 or more categories or attributes (such as price, style, and comfort) with category importances or weights to arrive at a single number that represents the net value of a choice under consideration.

**Category weight.** A scaling constant that indicates the importance or weight of a particular category or attribute relative to the total multiattribute value function. Category weights are indicated by the  $k_i$ s in the following equation for the additive multiattribute value function  $v$  of option  $a$ :

$$v(a) = \sum_{i=1}^n k_i v_i(a)$$

where the  $v_i$ s represent the single-attribute value functions for attribute  $i$  of option  $a$ . The index  $i$  varies from 1 to  $n$ , the total number of attributes considered.

**Importance weight.** A category weight based on the decision-maker's perception of how important the category is relative to other categories under consideration.

**Swing weight.** A category weight based on the decision-maker's perception of how important the category's swing in values (from worst to best) is relative to the swings in values for other categories under consideration.

**Weight correction due to scale.** An adjustment in category weight based upon the range  $r$  of a new or local scale relative to the range  $R$  of an original or global scale. For linear value functions the ideal correction factor is simply the ratio  $r/R$  so that (ideal normalized new weight) = (normalized original weight)( $r/R$ ).

**Range Sensitivity Index, RSI.** The RSI (Von Nitzsch & Weber, 1993) indicates the accuracy of the weight correction due to scale and is equal to 1.0 when the weights are adjusted optimally and equal to 0 when no weight adjustment is made. The farther the RSI is from 1.0, the poorer the correction (see Appendix).

Weights and scales are not independent and the elicitation techniques used must yield the appropriate mathematical relationship between the two. This has proven problematic. Those techniques advocated by Keeny and Raiffa (1976), by Clemen and Reilly (2001), by Goodwin and Wright (2001), and by many others, which are based on the use of *local scales*, tend to amplify small differences in attributes measured on natural scales, which may lead to erroneous conclusions. Attempts to mitigate the errors introduced by using local scales in conjunction with importance weights often focus on the Range Sensitivity Principle (RSP) which mandates that the category weights applied to each criterion should be adjusted so that they are proportional to the ranges of the alternatives for that criterion: small ranges should yield correspondingly small weights, and vice versa. However, people have trouble adequately adjusting the weights; every study reported in the literature indicates that the Range Sensitivity Principle is violated, often significantly, with Range Sensitivity Indexes rarely approaching 1.0 (ideal) and often well below 0.30 (Von Nitzsch & Weber, 1993; Fischer, 1995; Beattie & Baron, 1991; Yeung & Soman, 2005; Gedenk & Sattler, 2005); see Table 1. Thus, when local scales were used, category weights were often adjusted substantially less than that mandated by the Range Sensitivity Principle.

In many cases the low RSIs do not significantly affect the conclusions of a decision analysis. However, in situations when several alternatives are rated closely in one attribute and that attribute has a relatively high weight, significant decision errors may accrue. There is negligible literature that demonstrates these failures, and decision analysts continue to use swing weights and local scales regardless of low RSIs. It is our contention that the prescriptive approach of the RSP and decision analyses that are based on it are inconsistent with human psychology because people do not think in terms of local scales and it is the natural tendency for decision-makers to weight criteria using importance weights that they are reluctant to alter. A modification is required that embraces hu-

Table 1: Literature values for range sensitivity (RSI = range sensitivity index; ideal RSI=1.0)

Source	Range Sensitivity
Von Nitzsch and Weber (1993)	RSI=0.17–0.75; mean=0.34
Goldstein (1990)	“Relatively High”
Stewart and Ely (1984)	“Weak”
Beattie and Baron (1991)	In 5 of 6 experiments, attribute weights were insensitive to attribute range.
Fischer (1995)	RSI=0.12–0.78
Levin, Kim, and Corry (1976)	Range of stimuli had no effect on weight
Gabrielli and von Winterfeldt (1978)	Negligible range sensitivity
Gedenk and Sattler (2005)	RSI=0.07–0.73; mean=0.34

man psychology and that is not prone to errors due to low RSIs. Global Scaling satisfies these requirements and improves the utility of the existing normative model.

This research makes several contributions to the field of MCDA:

1. It demonstrates that conventional normative methods mandating local scales can lead to decision errors in certain situations.
2. It prescribes a modification (global scaling) that reduces these errors.
3. It demonstrates the proper procedure for constructing global scales.
4. It demonstrates the advantages of global scaling experimentally.

## 2 Theoretical

Basic multi-attribute choice scoring models require 4 steps: 1) the construction of a complete attribute tree, 2) the scoring of alternatives using subjective or objective scales, 3) the weighting or assignment of relative importance of the various attributes, and 4) the integration of these values into one net score for each candidate. In step 2, when local scales are used, differences in objective attribute values are typically transformed to use the full range of the attribute scale (typically 0–1, 0–10, or 0–100). Thus the poorest choice among the local option choices available, not among the entire *universe* of choices, would get a score of 0 and the best, 100. This forced transformation may over-emphasize the importance of small differences in attribute values and consequently lead to wrong conclusions. There does not appear to be a strong theoretical basis for local scales and their use has been based primarily on calculational convenience, on reducing the chance of an incorrect assumption of preferential independence by virtue of the smaller range, or on the argument that it facilitates decision-making by amplifying small differences (Hämäläinen,

2002; Fischer, 1995). Unfortunately, this amplification can lead to the wrong conclusion.

### 2.1 Relevant literature

There is substantial literature showing that the use of local scales precludes the use of importance weights in MCDA (see for example Goodwin & Wright, 2004) because importance weights will assign inappropriate weights to specific criteria when the range of values for that criterion is small, and vice-versa. The conventional prescriptive solution to this problem is an adjustment in the weights per the Range Sensitivity Principle via techniques such as swing weighting. In practice, though, decision makers typically under-adjust weights significantly. Because the methodology is fairly robust, this under-adjustment often does not affect the final outcome. In certain circumstances, however, the use of local scales leads to the wrong conclusion. Local scaling appears to be accepted as standard operating procedure for MCDA while global scaling is infrequently mentioned in the literature.

Four groups of researchers who do discuss global scaling are Bana e Costa, Lourenço, Chagas, and Bana e Costa (2008), Botta and Bahill (2007), Trainor and Parnell (2008), and Hämäläinen (2002). Bana e Costa et al. used global scaling (based not upon selection of extreme values but instead based upon identification of “good” and “neutral” values) in conjunction with swing weighting. They used ordinal pair-wise comparisons instead of cardinal comparisons and then used a computer program to translate into numbers. Botta and Bahill also described global scaling based upon legally imposed extreme values, maximum/minimum constraints imposed by customers, or the “highest and lowest values ever expected”; they also used swing weights.

Trainor and Parnell developed a constrained global scale whose extreme values were based upon “ideal” and “worst feasible” values for the number of people

required to operate a rocket system. They also used swing weighting. Hämäläinen discussed “actual,” “acceptable,” “available,” and “theoretically feasible” ranges which suggest global scales. We are unaware of researchers who used global scaling in conjunction with importance weights and we question the wisdom of using swing weights with global scales inasmuch as doing so appears to address scale range issues twice: once when assigning values based on global scales and again when assigning swing weights. If global scaling accurately maps relative values of the various choices then the use of importance weights should be all that is necessary for proper preference elicitation. Other than Bana e Costa et al., Botta and Bahill, Trainor and Parnell et al., and Hämäläinen, there is little literature discussing global scaling.

In other relevant discussions, several references (Belton & Stewart, 2002; Weber & Borcharding, 1993) admonish the practitioner to ensure that his selection of attribute weights is consistent with whichever scale is chosen. Some references (Belton & Stewart, 2002) state that local scales are fine for “roughing out” problems or for quick answers. Others (Gustaffson, 2000) note that linking attribute weights to the value scales may prove difficult. And, there are warnings that the use of local scales makes it difficult to subsequently add new choices whose values fall outside the range of the local scale. But nowhere does the literature discuss the outright decision errors that may accrue from local scaling and many researchers continue to use it as standard operating procedure (see e.g., Moshkovich et al., 2002; Roberts & Goodwin, 2002; and Phillips & Bana e Costa, 2007).

Several researchers have investigated the Range Sensitivity Principle and the effects of range on category weights. In 1976 Levin, Kim, and Corry studied the impact of stimulus range on weight using college students to assess student performance as a function of mid-term and final exam grades. They varied the reported range of test scores and found that weights did not vary with stimulus range. In unpublished work, Gabrielli and von Winterfeldt (1978) found negligible sensitivity of criteria weight to criteria range. Stewart and Ely (1984) used swing weighting to assess various pollution control results and found that the range sensitivity principle was violated significantly. They hypothesized that “The failure to meet the range-sensitivity requirement suggests that the elicited weights represented general values or attitudes toward the criteria, not specific tradeoffs among them.”

Goldstein (1990) studied local vs global interpretations of importance by examining graduate students’ preference for a variety of apartments as the range of rents varied from wide to narrow. He speculates that people may prefer global importance weights because they better

communicate “the structure of their preferences to other people” without depending on a local context. His experimental results indicated that subjects adjust weights as attribute ranges vary, but he did not calculate a RSI or determine if weights varied per the normative model. He concluded that people do not maintain global interpretations of importance.

Conversely, Beattie and Baron (1991) conducted a series of experiments in which subjects were asked to assess weights while provided varying degrees of information about attribute ranges. In their study, 5 out of 6 experiments showed no range sensitivity. The 6<sup>th</sup> showed substantial range sensitivity in a situation involving arbitrary scales of leadership and interpersonal skills that were intentionally constructed so that respondents could not relate them to any prior experience or knowledge. Beattie and Baron state, “In this case the surrounding stimuli are clearly relevant in making the value judgment, and thus it seems entirely reasonable to take them into account.” They note that the respondents’ judgments were “not entirely determined by the range of the attributes” and speculate that some anchoring on the mean value of each dimension was displayed. Beattie and Baron concluded that their data supported the concept of “true weight,” or weight that is invariant with context and they speculated that there is a moral basis for this. They focused on weight elicitation methods but did not address optimal scaling when using true weights. They also observed that decision makers experienced significant difficulty in making tradeoffs.

Von Nitzsch and Weber (1993) developed a Range Sensitivity Index (RSI) to measure the empirically observed adjustment of weights relative to the adjustment prescribed by the normative model. They found that the empirically observed adjustments were typically half those mandated by the model. They did not explore the decision errors that may accrue as a result. Weber and Borcharding (1993) reviewed the previous work of Von Nitzsch and Weber (1993), Fischer (1990), Beattie and Baron (1991) and others and concluded that in each study decision makers do not take range adequately into account when adjusting weights. They then draw the surprising (and in my opinion unfounded) conclusion that analysts should not use weighting methods that rely on importance judgments. They further concluded that there exists evidence for both local and global interpretations of attribute weight, but they do not propose an explanation for the disparate data. Mellers and Cooke (1994) also found invariance of attribute weight with range, but a sensitivity of scale factors to range.

Fischer (1995) explored the sensitivity of attribute weight to range and found that all weight elicitation techniques yielded sensitivities below that predicted by the normative model, although some came close.

Table 2: Automobile attributes for Example 1.

	Attribute importance weight	Accord	Saturn	Cavalier
Price (\$)	.7	16,100	16,000	15,900
MPG	.1	26	23	22
Performance (scale: 0–10)	.1	8	5	5
Style (scale: 0–10)	.1	7	5	4

Table 3: Automobile attributes adjusted to 0–10 scale.

	Attribute importance weight	Accord	Saturn	Cavalier
Price (\$)	.7	16,100→0	16,000→5	15,900→10
MPG	.1	26→10	23→2.5	22→0
Performance (scale: 0–10)	.1	8→10	5→0	5→0
Style (scale: 0–10)	.1	7→10	5→3.33	4→0

Tradeoff methods yielded the highest range sensitivity ( $0.63 < RSI < 0.78$ ), swing-weighting yielded intermediate range sensitivity ( $RSI = 0.62$ ), and direct importance weighting yielded the lowest range sensitivity ( $RSI = 0.12$ ). Fischer explained the differences in terms of a *value comparison hypothesis*: “The greater the degree to which a weight assessment task requires cross attribute comparisons of values or value differences, the more sensitive the evoked weights will be to the range of attribute values in the local decision context.” Fischer also posited that “...intuitive perceptions of attribute importance are independent of the range of outcomes in the local context or that people provide their own implicit context.” Yet Fischer argued in favor of local scales: “A local description is often the most natural because the range of outcomes in the local context may be so small relative to the global context that the local outcomes may appear indistinguishable.” He further developed the Range Sensitivity Principle which argues that attribute weights should vary in proportion to their ranges. Despite Fischer’s observation that perceptions of weight are independent of attribute range, and despite experimental determinations of RSIs that are between 22% and 88% below the optimum of 1.0, since swing weighting and direct trade-off weighting yielded RSIs closer to 1.0, he concluded that they both are preferable to importance weighting. However Fischer did not assess the benefits of using direct importance weighting in conjunction with a global scale.

Highhouse et al., (1999) found a significant impact of salary range on job choice. However they did not break their assessment procedure into weighting factors and attribute ratings. Pöyhönen and Hämäläinen (2001) compared several multiattribute weighting techniques but

could not determine a clear winner. They were unable to determine whether or not decision makers adequately adjust category weights for attribute range. Yeung and Soman (2005) evaluated range sensitivity as a function of attribute evaluability. They determined that greater evaluability led to greater sensitivity to range. They did not calculate RSIs or determine if their data fit the normative model.

The inevitable conclusion from all the literature is that normal people do not and cannot adequately adjust criteria weights for attribute range per the RSP. There are also substantial experimental and field data supporting the concept of global, true, or importance weights that people are reluctant to change. These data therefore suggest that local scaling in conjunction with swing weighting is inconsistent with human psychology. However, the literature does not discuss the decision errors that may be caused by the violations of the prescriptive model. Several examples illustrate these points.

## 2.2 Examples

**Example 1: local scales and range sensitivity index = 0 and 0.64 (SMART).** Certainly errors may occur with local scaling if weights are not adjusted for range. Suppose an individual is considering the purchase of a new car, and has settled upon an Accord, a Saturn, or a Cavalier (adapted from Clemen & Reilly, 2001, and Noonan 2004). Suppose further that the individual has decided that only 4 attributes are important to the decision: price, MPG, performance, and style. Thus there are 3 choices and 4 measures, and an attribute table may be constructed as shown in Table 2:

Table 4: Weights corrected using Range Sensitivity Principle, RSP (RSI=Range Sensitivity Index; Ideally RSI=1.0)

	Uncorrected global weights	Weights ideally adjusted per rsp to yield a RSI=1.0	Weights that would yield a RSI=0.62
Price	.7	.179	.507
MPG	.1	.205	.132
Performance	.1	.308	.181
Style	.1	.308	.181

To demonstrate possible errors, Table 2 has been set up to include one attribute (price) that is weighted heavily and whose alternative values are very close. Using local scaling, the next step is to adjust the subjective scores to maximize the differences among alternatives, transforming the range of each attribute to a full 0–10 range on a local scale (Table 3):

If no correction for range is made (viz RSI = 0), then applying the weights to the scores and summing yields a net weighted score of 0.3 for the Accord, 4.083 for the Saturn, and 7.0 for the Cavalier, and the Cavalier is selected as the best choice for this individual. Clearly, this conclusion does not make sense. The Cavalier is dominated by both the Saturn and the Accord in every category except price. Price is very important to the purchaser; however, the difference in prices of the 3 cars is insignificant (+/- 0.6%) and it is unlikely that any reasonable person would choose the Cavalier. Yet, because no range correction was made, the negligible differences in price have been assigned inappropriate significance. This is the crux of the problem when importance weights + local scales are used with no range correction.

In theory, this type of error is mitigated by the Range Sensitivity Principle (RSP) which mandates that the category weights be adjusted depending upon the range, and various techniques (such as swing weighting) are used for this. Typical literature values for RSI average between 0.2 and 0.4 (recall that ideal RSI=1.0) indicating substantial under-adjustment. But do these under-adjustments/low real-world RSIs significantly affect decision analysis conclusions, and if so, how high must the RSI be to ensure accuracy? The following calculations show that it must be surprisingly high; >0.62. If the uncorrected importance weights are adjusted for range according to the RSP following the method of Von Nitzsch and Weber (1993; see Appendix) using a global range for price of \$8,000, one obtains Table 4.

The middle column of this table list the weights ideally adjusted to yield a Range Sensitivity Index (RSI) of 1.0. The last column of this table lists the weights arbitrarily adjusted to yield a RSI of 0.62. Certainly, using the ideal values corresponding to RSI=1.0 (middle column) would

Table 5: Net scores with weights corrected using RSI=0.62.

Attribute/Weight	Accord	Saturn	Cavalier
Price (\$)/.507	0/0	5/2.535	10/5.070
MPG/.132	10/1.32	2.5/0.330	0/0
Performance (scale: 0–10)/.181	10/1.81	0/0	0/0
Style (scale: 0–10)/.181	10/1.81	3.33/.603	0/0
Total weighted score	4.94	3.47	5.07

yield the correct decision, that is, the Accord is the best car. People almost never adjust the weights to this ideal degree. Using the more realistic adjusted weight values corresponding to RSI=0.62 yields Table 5.

This indicates that the Cavalier is again selected as the best car, showing that even with RSIs as high as 0.62 the wrong conclusion may be drawn. Thus, in this case *RSIs must be greater than 0.62 to ensure accurate conclusions when the choices among a heavily-weighted attribute are close in value.* RSIs are rarely this high. This result underscores the potential weakness of local scaling techniques that rely upon the range sensitivity principal.

**Example 2: global scaling without the range sensitivity principle.** Using automobile price as in the example above, the 3 car prices are \$15,900, \$16,000, and \$16,100. Now we may ask the decision-maker, “What car price would make you extremely happy/satisfied and that you would rate as a 10 on a 0–10 scale?” The answer might be “\$12,000” instead of the price of \$15,900. This \$12,000 price would then be assigned a value of 10 on the global scale. Similarly, the individual might rate a price of \$20,000 (instead of \$16,100) as extremely poor and worthy of a 0; \$20,000 would then be assigned a value of 0 on the global scale. A 0–10 scale is still used to normalize the objective values. However, now instead of the *option* extremes being mapped to (0,10) the *global* extremes are mapped to (0,10), and the actual prices of the 3 cars are transformed to the 0–10 **global** scale via

Table 6: Automobile attributes using global scales.

Price	Hypothetical car A	Accord	Saturn	Cavalier	Hypothetical car B
Natural score	20,000	16,100	16,000	15,900	12,000
Local score	–	0	5	10	–
Global score	0	4.875	5.00	5.125	10

linear interpolation.<sup>1</sup> (Note that “global” in this context refers to the locus of the decision-maker’s experiences, imagination, or aspirations, not the locus of *all* possible values.) Doing so yields Table 6.

The use of the global scale provides new scores that are much better indicators of the subjective values of the 3 prices than were the old scores. Doing this for MPG as well (using 12 mpg and 35 mpg as the extremes of the global MPG scale) and applying these new global scores to the summary table yields Table 7.

Now the Accord is clearly the best choice. In this case, the small differences in car price are weighted appropriately, not artificially inflated to emphasize small differences. The Accord is clearly the superior car, dominating the other cars in every area except price, for which all 3 cars have functionally identical values. This adjustment to the subjective rating technique prevented the wrong conclusion from being drawn.

The determination of both the extreme values of a global scale and the swing weights for a local scale is subjective. Experiments are needed to determine if it is easier for people to properly assess global scale extremes than to assess trade-offs among attributes for local scales.

The above examples show that:

1. Using a Range Sensitivity Index (RSI) of 0 can provide the wrong answer when local scales are used.
2. Using a RSI as high as 0.62 in SMART can similarly provide the wrong answer.
3. Using Global Scaling and Importance Weights which are not a function of attribute range provides the correct answer.

Decision-makers rarely adjust category weights sufficiently to compensate for differences in attribute ranges, and people tend to rate alternatives based upon some intuitive concept of global (not local) scales in conjunction with importance weights that remain fixed. (Interestingly, Von Nitzsch & Weber (1993) found that weights elicited according to some concept of an “intuitive range” were not better predictors of decision-makers’ preferences. However, they did not elicit global extremes for

<sup>1</sup>For simplicity, linear value functions are assumed. Just as for local scales, standard methods may be used to accommodate non-linear value functions (see, e.g., Clemen & Reilly (2001), Keeney & Raiffa (1976), or Trainor and Parnell (2008)).

Table 7: Net scores using global scales.

Attribute/Weight	Accord	Saturn	Cavalier
Price (\$)/.718	4.875/3.500	5/3.590	5.125/3.680
MPG/.051	6.1/0.31	4.8/0.24	4.31/0.22
Performance (scale: 0–10)/.131	10/1.3	0/0	0/0
Style (scale: 0–10)/.096	10/0.96	3.33/0.32	0/0
Total weighted score	6.07	4.150	3.900

attribute scales. Thus their “intuitive ranges” were in fact local ranges.)

### 2.3 Global scales

Several types of global scale may be inferred.

*Experiential Global Scale.* An experiential global scale is based upon an individual’s personal experience with or knowledge of a particular subject. The knowledge may derive from what the individual has experienced, read, seen, or heard. The price of a dozen eggs is a good example: an individual might develop an experiential global scale for a dozen eggs with global extreme values of 80¢ and \$3.50 based upon personal experience with egg prices or based upon a newspaper article or TV show that listed the prices for eggs in various countries. The extreme values thus represent prices that the individual believes actually exist (or existed). A maxim for this type of global scale might be “The best and worst prices I know of.”

*Imagined Global Scale.* An imagined global scale is based upon the best and worst values an individual can imagine exist in reality. Continuing with the egg example, an individual might imagine that the best price imaginable for a dozen eggs might be 10¢ in some rural farm area of Asia while the worst price might be \$10.00 in Antarctica or northern Siberia. A maxim for this type of global scale could be “The best and worst prices I can imagine on earth.”

*Aspirational Global Scale.* An aspirational global scale is based upon the best and worst values that an individual believes he or she could realistically achieve, that is values that are within his means or capability. Aspirational global scale-based automobile prices, for example, might be \$12,000 and \$90,000, meaning that this individual believes he could never find a new car for less than \$12,000 and that the maximum he could afford for one is \$90,000. A suitable maxim might be “The best and worst prices I could ever hope to achieve.”

*Universal Global Scale.* A universal global scale is based upon the best and worst values conceivable. For eggs, for example, these values might be \$0 and \$10 trillion. Because they do not typically reflect personal values or experience and because the differences among real-world choices are usually miniscule when using them, universal global scales are not particularly useful in decision analysis. A maxim for this type of scale could be “The best and worst prices that could hypothetically exist anywhere in the universe.”

*Constrained Global Scale.* A constrained global scale is based upon extreme values that are specified. The specifications may be legal values (e.g., a 1-pound box of cereal must weigh between 0.950 and 1.050 pounds), customer constraints (e.g., the kitchen island length must be between 66 and 74 inches), specified component cost (e.g., the flux capacitor shall have a minimum manufactured cost of 79¢ and a maximum cost of \$2.83), etc. A suitable maxim might be “The best and worst prices allowed.” Note that in this case the most desirable value might be in the middle of the range and the least desirable values might be the 2 extremes.

There are undoubtedly other types of global scale as well. People use different types of global scale depending upon the situation (see “experiments” section). If an individual has reasonable experience in the topic, she may use an experiential global scale. For example, in deciding if \$1.20 is a good price for a dozen eggs, a person might invoke her past experience with egg prices. On the other hand, when confronted with hypothetical or speculative issues for which the individual has little direct or referential experience, she may use an aspirational global scale. For example, the question “Which is more important to you: saving lives or saving money, and how many times?” may elicit a response based on how many lives the individual feels she may ultimately have the ability to save and how much money she may have the ability to save within her lifetime. Most people do not have direct experience trading off saving money for saving lives.

Global scales are not necessarily fixed, but may vary over time. In 1973, a colleague thought that 40¢ and 15¢ were terrible and excellent prices for a gallon of gasoline and those values represented the extremes of his experiential global scale. Today his extreme values are \$4.00

and \$1.25 and they are changing weekly as the price of crude oil fluctuates. The global scale ranges may either swell over time (as with gasoline) or shrink. In 1980 another colleague thought that 25% and 5% were excellent and poor annual salary increases. Today, her experiential global extremes are 8% and 0%.

Our feelings and perceptions of “good” and “bad” change as we experience new things, as we learn more, and as the world changes around us. We cannot use a 1970s global scale to decide today which are good and bad prices or quality levels for cars. As individuals’ perceptions of “good,” “bad,” and “mediocre” change, so do their global scales. This is another potential advantage of global scales over local scales. Global scales can change over time to reflect changes in perceived values; local scales cannot.

Global scales may be influenced by the prominence effect (Tversky, Sattath, & Slovic, 1988) and by cognitive biases such as representativeness, availability, and anchoring. These are topics for future research.

*Global Scale Construction.* Global scales may be constructed by asking the decision-maker to select an attribute value from the natural scale that he would describe as “excellent” or worth a score of 10 and another attribute value that he would describe as “terrible” or worth a score of 0. The analyst need not specify whether the decision-maker should use an experiential, aspirational, or other type of global scale; but he may describe these types of global scale if it helps the decision-maker. Non-linear value functions may be accommodated by asking the decision-maker to first fix extreme values of 0 and 10 and then to fix several intermediate values between 0 and 10. It is not necessary to select the extreme values in order to adequately specify a global scale. Bana e costa et al. (2008) used global scaling based not upon selection of extreme values but instead based upon identification of a “good” value (set =100) and a “neutral” value (set =0.) Values of actual choices may then be <0 and >100.

### 3 Experiments

No experiments were conducted to demonstrate that the Range Sensitivity Index is invariably too low because ample literature shows this (Table 1). However, four experiments were conducted to:

1. determine if global scaling is a natural, intuitive approach that is readily embraced by decision-makers and that provides appropriate answers;
2. determine if global scaling together with importance weights provides better decision results than local scaling together with swing weights when

Table 8: Attribute data for experiment.

	Accord	Saturn	Cavalier
Price (\$)	23,100	23,000	22,900
MPG	26	23	22
Performance (scale: 0–10)	8	5	5
Style (scale: 0–10)	7	5	4

the choices among a heavily-weighted attribute are close in value.

These experiments were intentionally constructed to focus on situations where local scaling may be deficient: situations wherein several alternatives are rated closely in one attribute (e.g., price) and that attribute has a relatively high weight. For the first experiment, the data presented in Table 8 reflecting the attributes of 3 cars were presented to 42 individual decision-makers. The decision-makers were graduate students and staff at Worcester Polytechnic Institute, Worcester, MA in the summer and fall of 2007.

The decision-makers were informed that both the objective and subjective ratings had been determined by experts from a national consumer testing organization. Importance weights and global scales were used in a SMART-type analysis. The ratings for Performance and Style were left as-is, as they already reflect use of a global scale. For price ratings, the decision-makers were each asked to imagine a hypothetical car A with a price that they would regard as very poor for the type of car they are considering (i.e., a regular production family sedan), and a price that was excessively high based on their experience and knowledge of automobile prices. They were told that this high-price limit did not need to include any of the 3 current choices, but could come from their own personal experience with cars. They were then asked to imagine a price for a hypothetical car B that they would regard as excellent, one that was quite low, again, based upon their personal experience and knowledge. These extreme prices were then mapped to 0 and 10. The rating values of the 3 cars actually under consideration were then determined by interpolation.

Global scale ratings for MPG were determined similarly: each respondent was asked to imagine a MPG figure that they viewed as very poor; this value was mapped to a rating value of 0. The respondents were also asked to imagine, based on their own personal experience, an MPG value that they viewed as excellent, and that value was mapped to 10. The actual ratings of MPG for the 3 cars under consideration were then determined by interpolation.

Typical results for price and MPG global scale extremes (determined by averaging all responses and then rounding) are depicted in Table 9, which also shows the ratings for all 4 attributes of all 3 cars based upon *global* scales.

Next, importance weights were elicited from each decision-maker. Decision-makers were first instructed to disregard data for this particular example and just consider the 4 attributes: price, mpg, performance, and style. They were then instructed to rank the 4 attributes in order of importance, from most important to least important. Next, they were asked to assign their most important attribute a weight of 100. Then, they were asked to assign relative importance weights to the remaining 3 attributes, relative to the 100 of their most important attribute. For example, if they felt that their second most important attribute were half as important as their most important attribute, they should assign it a weight of 50. The 3<sup>rd</sup> and 4<sup>th</sup> attributes were assigned weights similarly and the weights were then normalized to sum to 100. Note that this assignment of importance weights does not take into account the ranges of values of the 3 cars under consideration. 100% of the respondents were able to determine importance weights in this manner. For each candidate car, the rating for each attribute was multiplied by the importance weight of that attribute, and the results summed over all 4 attributes to yield a net score.

Because the Saturn and Cavalier had very similar criteria ratings in all 4 categories, one would expect an accurate analytical tool to rate them similarly. However, the Cavalier is dominated by the Saturn in all areas except for price (for which the 2 cars are within 0.5%) and therefore one would expect a good analytical tool to rate the Saturn higher than the Cavalier, albeit close to it. Further, because both cars are dominated by the Accord in all categories except price (and their prices are all within 1%) one would expect an accurate analytical tool to rate the Accord as superior to both the Saturn and the Cavalier. Results indicated that, using Global Scaling + Importance Weights, 100% of the decision-makers chose the Accord, 0% chose the Saturn, and 0% chose the Cavalier, which is consistent with our expectations and with our knowledge of the characteristics of the 3 cars. In addition, 100% of the decision-makers rated the Saturn as superior to the Cavalier and 92% of the respondents rated the Saturn and Cavalier within 15% of each other. Furthermore, >70% of the decision-makers commented that the assignment of importance weights was straightforward and intuitive (there were -0- negative comments,) and 100% of respondents were able to select reasonable extreme values for price and mpg that represented their best and worst global values. (Hypothetical Worst Price ranged from \$22,000 to \$60,000 with a mean of \$31,283.30, Hypothetical Best Price ranged from \$10,000 to \$22,000 with a mean of

Table 9: Typical experimental results.

	Hypothetical Car A	Accord	Saturn	Cavalier	Hypothetical Car B
Price (\$)	31,000	23,100	23,000	22,900	18,000
Price Global Score	0	6.077	6.154	6.231	10
MPG	18	26	23	22	36
MPG global score	0	4.444	2.778	2.222	10
Performance global score	0	8	5	5	10
Style global score	0	7	5	4	10

Table 10: Hypothetical worst car for swing weighting experiment.

	Accord	Saturn	Cavalier	Hypothetical worst car
Price (\$)	23,100	23,000	22,900	23,100
MPG	26	23	22	22
Performance (scale: 0–10)	8	5	5	5
Style (scale: 0–10)	7	5	4	4

\$18,018.90, Hypothetical Worst MPG ranged from 5.0 to 22.0 with a mean of 17.6, and Hypothetical Best MPG ranged from 26.0 to 60.0 with a mean of 35.5.) Global scaling with importance weights provided excellent results in this instance and appears to be a natural, intuitive approach that is readily embraced by decision-makers.

For comparison, swing weights were also elicited, following the method of Goodwin and Wright (2004). The decision-makers were asked to imagine a hypothetical car with the worst values for each attribute, as shown in Table 10.

They were then asked if they could choose one of the 4 attributes and change it to its *best* level as shown in Table 10, which would they choose? After this, the decision-makers were asked which attribute they would next choose to move to its best level, etc, until all 4 attributes had been ranked. The most important attribute was then assigned a weight of 100. Respondents were next asked to compare for the second most important attribute a swing from its worst value to its best value with a similar swing for the most important attribute and to weight that relative to the weight of 100 for the most important attribute. For example, if the decision-maker rated style as most important (weight=100) and performance as second most important, the question would be, “How important is a swing in performance from 5 to 8 relative to a swing in style from 4 to 7?” This was

then repeated for the remaining 2 attributes to determine swing weights, which were then normalized so that they summed to 100.

The swing weighting + local scale results were not as good as the importance weighting + global scale results. For swing weighting, 41 (98%) of the decision-makers chose the Accord (vs 100% for importance weighting). This difference is not statistically significant at  $\alpha < .10$ . However 6 (14%) preferred the Cavalier to the Saturn (vs 0% for importance weighting (significant at  $\alpha < .013$  using Fisher’s exact test)) which is inconsistent with our expectations and knowledge of the 3 cars. In addition, 67% of the decision makers preferred importance weighting to swing weighting (21% preferred swing weighting and 12% established no preference.) Of those who preferred importance weighting, typical comments mentioned that importance weighting was “more intuitive,” “less confusing,” “more straightforward,” and “easier to work with” than swing weighting. Thus, relative to swing weighting + local scaling, importance weighting + global scaling provided results that more closely matched our expectations regarding the “correct” decisions and was rated as easier to work with by the majority of respondents.

Two more similar experiments were conducted in 2009 using plasma TVs and electric guitars as the items to be considered for purchase (see Tables 11 and 12). These experiments were constructed with the hope that the respondents would be more knowledgeable about some items (TVs) than others (electric guitars) and that their approaches to constructing global scales would therefore vary with their comfort level. The mathematical structure of the TV and guitar experiments was identical to that of the car experiment: the first choice dominated the other 2 choices in all areas except the financial parameter (for which all 3 choices agreed within 1%) and the second choice dominated the third choice in all areas except financial (for which the 2<sup>nd</sup> and 3<sup>rd</sup> choices agreed within 0.5%).

One would expect to see increased errors with the local scaling/swing weighting technique when the elicited swing weight of the financial parameter is high relative to

Table 11: Plasma TV experiment.

	Panasonic	Sony	Hitachi
Price (\$)	2,009	1,999	1,990
Repair frequency (%)	6%	10%	11%
Picture quality (scale: 0–10)	8	5	5
Sound quality (scale: 0–10)	7	5	4

Table 12: Electric guitar experiment.

	Fender	Gibson	Rickenbacker
Price (\$)	505	495	515
Sound quality (1–10 scale)	7	6	9
Construction Quality (1–10 scale)	7	7	9
Warranty (months)	24	12	36

the elicited swing weights of the other parameters. When this is not so, one would expect local scaling and global scaling to yield similar results.

The results of these experiments are summarized in Table 13.

The “Ideal” results column represents results that should obtain based upon dominance or near-dominance. The Global Scaling + Importance Weight technique never yielded poorer results than the Local Scaling + Swing Weight technique and yielded significantly better results in 2 out of 3 experiments at  $\alpha < 0.013$  while yielding equivalent results in the electric guitar experiment (for that experiment, very few respondents weighted the price high relative to the other swing weights; thus there was little difference between local and global scaling).

For the automobile and plasma TV experiments, it is helpful to understand the reasons for the poorer results of the swing weighting/local scaling technique. For these experiments, the individual response data were separated into 2 sets: Group A comprised the data for which the 2 techniques (swing weighting + local scales vs importance weighting + global scales) agreed (that is, indicated the same preferences) and Group B comprised the data for which they differed. Table 14 shows the median importance weight, global scale range, swing weight, and local scale range for price broken out by data sets A and B:

Recall that the Importance Weight + Global Range technique gave the ideal answer 100% of the time so where the 2 techniques disagree it is the local scale/swing

weighting technique that is suspect. Note that there are no significant differences in global ranges for groups A and B so the benefit does not derive from broader global ranges, nor are the differences in importance weights significant. However, there is a dramatic difference between the data sets in the elicited swing weights: when local scaling yields the correct preference, the swing weights are low but when local scaling indicates the wrong preference, the swing weights are high. This indicates that the local scaling errors are caused by inadequate reduction of swing weights for the small local scales used.

These experiments support the superiority of Global Scaling + Importance Weights over Local Scaling + Swing Weights when several alternatives are rated closely in one attribute (e.g., price) and that attribute has a relatively high weight. Further, for these experiments, >61% of respondents rated the Importance Weighting technique as more straightforward and more intuitive than the swing weighting technique. Although user preference may not be a good indicator of the superiority of any one technique, in this case the lower comfort level with swing weighting suggests that it is harder to use and may explain the poorer results associated with it.

### 3.1 Global scale construction and correlation with subject matter familiarity

An attempt was made to determine how individuals construct global scales. For the last 2 experiments, respondents were asked to rate their familiarity with the subject matter on a scale from 1 (I am not familiar at all) to 4 (I am an expert on these items). For the electric guitar experiment, average respondent familiarity was 1.6 and for plasma TVs average familiarity was 2.5. Respondents were also asked what basis they used to determine their global scale extreme values. Choices were:

1. Items you actually owned, used, or experienced
2. Items you read about, heard about, or saw somewhere
3. Items you imagine must exist somewhere
4. Items you imagine could be built or developed somewhere
5. Items you think are within your capability to own
6. Other

Choices 1 and 2 would indicate an experiential global scale, choices 3 and 4 indicate an imagined global scale, and choice 5 indicates an aspirational global scale. One or more choices from 1–5 was cited as the basis for global extreme values in 100% of the responses; no responses

Table 13: Summary of experiment results.

Experiment	Preferences	Global scaling results	Local scaling results	“Ideal” Results
Automobiles	% preferring Accord over the others:	100%	97.6%	100%
	% preferring Saturn over Cavalier:	100%	85.7%	100%
Plasma TVs	% preferring Panasonic over the Others:	100%	100%	100%
	% preferring Sony over Hitachi:	100%	76.7%	100%
Electric Guitars	% preferring Rickenbacker over the others:	100%	100%	100%
	% preferring Fender over Gibson:	97.6%	95.1%	100%

Table 14: Comparison of experimental results for price broken out by data for which the 2 scaling methods (swing weighting + local scales vs importance weighting + global scales) agreed and disagreed.

Experiment		Median Importance Weight	Median Global Range (\$)	Median Swing Weight	Median Local Range (\$)
Plasma TVs, n=44	Data Set A: The 2 Techniques Agree	.27	1,505	.10	19
	Data Set B: The 2 Techniques Disagree	.32	1,625	.32	19
Automobiles, n=41	Data Set A: The 2 Techniques Agree	.32	10,000	.11	200
	Data Set B: The 2 Techniques Disagree	.36	10,000	.33	200

cited “other.” For each level of familiarity (1–4) the number of respondents that based their global scales on experience, imagination, or aspiration was tallied. The results are tabulated in Table 15 and plotted in Figure 2, which shows the number of respondents who used each type of global scale as a function of respondents’ familiarity with the subject matter.

The results indicate that experiential and imagined global scales are much more common than aspirational scales (53% of responses indicated experience as the basis for their global scales; 41% indicated imagination as the basis, and 6% indicated aspiration). Results also show that as familiarity with subject matter increases from 1 (unfamiliar) to 4 (expert), respondents (not surprisingly) tend to favor experiential vs imagined global scales. Thus there is a strong correlation between familiarity with subject matter and the basis used for constructing global scales.

Interestingly, several respondents used a combination of bases to determine their global scale extremes: one basis (e.g., experiential) for their low extreme and another (e.g., aspirational) for their high extreme. The frequency

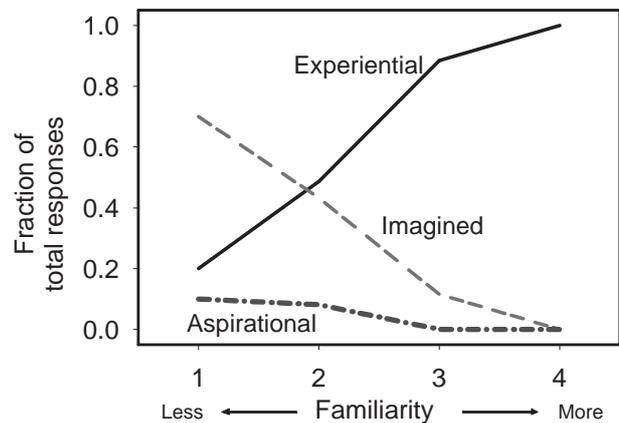


Figure 2: Type of global scale vs respondent familiarity with subject matter

with which respondents used multiple bases to construct global scales correlated with familiarity. Only 9.1% of respondents used multiple bases for the guitar experiment (1.6 average familiarity) while 20.5% used multiple bases

Table 15: Basis used for global scales as a function of respondents' stated familiarity with the subject matter

Stated familiarity with subject matter	Global scale basis-number of responses			
	Experiential	Imagined	Aspirational	Total responses
1 (Unfamiliar)	6	21	3	30
2 (Somewhat familiar)	18	16	3	37
3 (Quite familiar)	23	3	0	26
4 (Expert)	5	0	0	5
Totals:	52	40	6	98

for the TV experiment (2.5 average familiarity). There was no apparent consistency regarding which basis was used for best or worst extreme values. Why and when individuals use a combination of psychological bases to construct global scales are topics of future research.

These experiments demonstrate that people can construct explicit global scales when appropriately prompted and that experiential and imagined global scales are the most common. They further suggest that when respondents are familiar with the subject matter they tend to use experiential global scales; as familiarity decreases respondents rely more upon imagined global scales. Finally, instead of being based on any single factor, global scale construction is sometimes based on a combination of experience, imagination, and aspiration.

## 4 Discussion

Certainly there must be a mathematical relationship between attribute weight and attribute range for normative decision-making. Logical choices would be either local scales in conjunction with local weights that vary in proportion to the scale ranges, or global scales that correspond to global or importance weights. In the local model the difficulty is in accurately assessing tradeoffs of weight vs. range among categories, while in the global model the difficulty is in accurately identifying the extreme values of the global scales and meaningful importance weights. The preferred model should be the one that yields better decisions. In the 3 experiments conducted for this article, the global model performed better than the local model in 2 experiments and as well as the local model in 1 experiment.

### 4.1 The psychological cause of errors with local scaling and swing weighting

Arguably, the better a decision theory reflects human psychology, the better will be the results. The remapping of natural scale ratings to local values of 0 (worst) and 10

(best) seems to be inconsistent with the way people think. When asked to rate 2 alternatives on a scale of 0–10, most people provide results that are intermediate to the extremes of 0 and 10 demonstrating that they are thinking globally; that is, they have reference data that are outside the scope of the current choices and they evaluate alternatives within the larger, global scale of choices. (Another potential explanation is the psychological tendency to avoid extreme values, as noted in Parducci's [1965] range-frequency theory). However, the current data do not support that explanation: in independent experiments in which 42 subjects were asked to rate the food quality of 2 restaurants on 0–10 scales (without guidance regarding local or global scales), 88% of respondents explained that they developed their ratings by comparing the 2 restaurants to other restaurants with which they were familiar. When this experiment was repeated using cars instead of restaurants, 93% said that they rated the car quality based on either their personal knowledge of the quality of cars *not* included in the choices or based on what they had *heard or read about* cars *not* included in the current choices. These experiments indicate that, when asked to evaluate alternatives, individuals naturally tend to think globally, not locally, and bring their life experience to bear on the decision.

Swing Weighting (Goodwin & Wright, 2004; Belton & Stewart, 2002; Von Winterfeldt & Edwards, 1986) relies upon the oft-violated Range Sensitivity Principle (RSP) to elicit category weights. Although Gedenk and Sattler (2005) found no demographic explanation for the frequent violation of the RSP, there could be several reasons.

First, it may be that the mental trade-off calculations required for swing-weighting or linking pins are beyond the capabilities of most decision-makers. Assigning relative importance to *swings* in disparate attributes may be more confusing than simply assigning relative importance to the attributes themselves. In our experiments, >61% of the test subjects preferred importance weighting to swing weighting and expressed feeling of confusion or complexity when using swing weighting.

Second, the literature suggests that decision-makers tend to interpret category weights as intrinsic values that should not vary with the situation. Gabrielli and von Winterfeldt (1978) concluded that “people possess implicit notions of attribute importance that are independent of the specific decision context and that depend instead on a globally defined set of plausible alternatives and attribute ranges”. Similarly, Stewart and Ely (1984) concluded, “The failure to meet the range-sensitivity requirement suggests that the elicited weights represented general values or attitudes toward the criteria, not specific tradeoffs among them.” If the importance of various criteria changes depending upon the ranges, it implies that individuals have situational (vs. fixed) values. This has a negative connotation that most people resist. Therefore changing the weights forces an individual to admit socially unacceptable thinking. This manifests as  $RSIs \ll 1.0$ .

Third, swing weighting creates psychological conflict in decision makers: categories that are thought important for a decision may be assigned negligible weight. Analysts view criteria weights not as indicators of fundamental importance, but as decision-making tools that are free to vary if that facilitates decision-making. (Goldstein, 1990, calls these “paramorphic weights.”) We believe that this distinction creates dissonance and confusion in some decision-makers and that this dissonance results in failure of the RSP and concomitant poor decisions. For example, Schoner, Wedley, and Choo (1992) argue that safety in bridge design becomes *unimportant* as different designs exceed a safety standard by greater and greater amounts. This is accurate only from an analyst’s perspective. Safety remains vitally important to the decision-maker; it is small differences in safety that become unimportant, especially as all options measure farther and farther from a standard. This important psychological (and political/sociological) distinction is not violated so long as global scales (instead of local scales) are used.

These speculative reasons for failure of the Range Sensitivity Principle must be validated with further experiments. In any case, a decision technique that embraces natural human thought processes (*viz* a tendency to think globally when rating alternatives and a preference to weight criteria using invariant importance weights) will likely yield better results than one that does not, as evidenced by the above experiments.

## 4.2 The psychological basis for global scaling

As we go through life, we accumulate knowledge in many areas: price of groceries, price of gas, entertainment qual-

ity of movies, gas mileage of various cars, restaurant food quality, comfort of sofas. We then subconsciously construct and internalize global scales based upon this knowledge such that it is easy for us to render an absolute judgment on a new datum by locating it on our internal global scale. Blumenthal (1977) explains that “... absolute judgment... involves the relation between a single stimulus and some information held in short term memory about some former comparison stimuli or about some previously experienced measurement scale...” Indeed, we make absolute judgments all the time: most people would rate a price of \$12 for a box of cereal as very poor and a price of \$5,000 for a new car as very good. We are able to do this because we carry with us the former comparison stimuli within which we assess price; we carry with us global price scales for cereal and cars. Those global scales include price endpoints representing extremes that we would value as 0 or 10 on a 10-point scale. The extreme values are often not explicitly stated or even acknowledged; however they exist implicitly. It is the analyst’s job to expose them. The need for contextualization is so strong that even when we don’t have direct experience with a subject, we construct global scales via imagination or aspiration. It seems that we humans *must* frame our situations to deal with the world.

In a typical decision analysis situation, one may ask the decision-maker to use all her knowledge and history to determine to what natural value (not necessarily among the current option set) she would assign a value of 0 and to what natural value she would assign a value of 10 (see Figure 1.)

People make such subjective assessments frequently; every time they rate something on a scale of 0–10. The principal task of the analyst is to ensure that the extreme values selected really do represent what the decision maker views as worth ratings of 0 and 10. The accuracy with which this is possible must be confirmed by experiment.

Along with the exposition of the decision-maker’s pertinent global scales, meaningful importance weights must be elicited. The use of importance weights is often criticized because of lack of clarity: when a decision-maker says that saving lives is 10x as important as saving money, the factor of 10 seems arbitrary without an understanding of the ranges of lives and money under consideration. But we speculate (and plan on verifying) that individuals *do* consider ranges (albeit subconsciously) when articulating relative importance.

When someone articulates relative importance, it is necessary to determine the underlying context. When an individual is asked whether saving lives is more important than saving money, she will usually first apply a context: personal, corporate, public, or other. If personal,

she will then address the question within the context of her own aspirational global scales for saving lives and saving money. For example, she may feel that it might be within her realm of influence to somehow save between 1 life and 1000 lives; and these are the lives of “typical” people like herself. Similarly, she might feel that it is within her power realistically to save between \$10,000 and \$100,000. This entire contextualization process may occur within a split second or perhaps only subconsciously. Within the context of those global scales, she would be entirely justified to then state that saving lives is 10x as important as saving money. The global scales are rarely (if ever) elicited and their existence in our subconscious has not been validated, despite their logic. However, if we challenge a statement like “saving lives is 10x as important as saving money” by using outlandish figures such as trillions of dollars in exchange for the life of a mass murderer, the decision-maker is likely to say, “Well, I didn’t mean for people like *that* or dollar amounts like that,” which means that *some* ranges of people and money *were* in the decision-maker’s mind, albeit subconsciously. Thus, everyday statements of relative importance imply the existence of concomitant subconscious global scales.

Similarly, when someone says that automobile performance is twice as important as style, it is not arbitrary; it is with the subconscious awareness of experiential global scales for both style and performance for that class of car. In other words, based on personal experience, that person has subconscious benchmarks in mind for superior (and atrocious) style and performance — and these benchmarks represent the extremes of the global scales. Within the context of those global scales for performance and style, the individual may fairly state that one is twice as important as the other.

Thus *the existence of implicit global scales in every individual’s mind allows us to make valid statements of relative importance such as “Automobile performance is twice as important as style” or “Saving lives is 10x as important as saving money”*. Such statements are meaningful provided that we can determine the implicit global scales on which they are based.

The hypothesis that most individuals articulate importance weights based on the existence of subconscious personal global scales must be validated by future work. However, this model helps explain the reluctance of decision-makers to vary category weights once articulated and the concomitant errors associated with swing weighting. And, although the psychological underpinnings remain to be validated, in this study we have demonstrated that, in certain situations, global scaling + importance weighting potentially provides better results than local scaling + swing weighting.

## 5 Conclusion

Multi-attribute choice scoring model techniques are subject to errors from the subjective rating techniques used to construct attribute scales when local scales (instead of global scales) are used. The Range Sensitivity Principle does not adequately address scale ranges in determining appropriate category weights.

The situation may be avoided by using global scales instead of local scales — it appears easier for decision-makers to accurately assess extreme values of global scales in conjunction with fixed (importance) weights than to accurately make tradeoffs among different categories using local scales. Analysts should therefore focus on eliciting importance weights in conjunction with the extreme values of global scales inasmuch as they are consistent with psychological perceptions of value and importance.

Future work should examine the benefits (or lack thereof) of using global scales in conjunction with swing weights. Additional work should explore the construction of global scales, including a study of the influence of cognitive biases, the correlation of types of global scale with subject matter familiarity, and the reasons that individuals sometimes use combinations of psychological bases to determine global scale extremes.

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## Appendix: Calculation of range sensitivity index (RSI) and optimal local weights

### Definitions

$\lambda_i$  = local (or corrected for range) weight of characteristic  $i$ .

$\gamma_i$  = uncorrected importance weight of characteristic  $i$ .

' indicates empirical value.

\* indicates ideal (optimal) value.

$r_i$  = local (or new) range of values for characteristic  $i$ .

$R_i$  = global (or original) range of values for characteristic  $i$ .

$$m_i = \frac{\lambda_i^*/(1 - \lambda_i^*)}{\gamma_i/(1 - \gamma_i)}$$

$$m_i^{emp} = \frac{\lambda_i'/(1 - \lambda_i')}{\gamma_i/(1 - \gamma_i)}$$

$$RSI_i = \text{Range Sensitivity Index} = \frac{m_i^{emp} - 1}{m_i - 1}$$

### Equations

From Fischer's (1995) equation (9) it may be shown that for linear value functions,

$$\lambda_i^* = \frac{\gamma_i \frac{r_i}{R_i}}{\sum_{i=1}^n \gamma_i \frac{r_i}{R_i}}$$

This equation may be used to calculate ideal local weights as a function of ranges and importance weights.

From Von Nitzsch and Weber's (1993) definition of RSI one may show that

$$RSI_i = \frac{\frac{\lambda_i'}{1 - \lambda_i'} - \frac{\gamma_i}{1 - \gamma_i}}{\frac{\lambda_i^*}{1 - \lambda_i^*} - \frac{\gamma_i}{1 - \gamma_i}}$$

This equation may be used to calculate range sensitivity index as a function of observed local weights, ideal local weights, and uncorrected importance weights.