The C-OAR-SE procedure for scale development in marketing

John R. Rossiter

University of Wollongong, jrossite@uow.edu.au

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John R Rossiter

- School of Management, Marketing and Employment Relations, University of Wollongong, Northfields Avenue, Wollongong NSW 2522, Australia
- Department of Marketing Management, Rotterdam School of Management, Erasmus University, P.O. Box 1738, 3000 DR Rotterdam, The Netherlands

Abstract

Construct definition, Object classification, Attribute classification, Rater identification, Scale formation, and Enumeration and reporting (C-OAR-SE) is proposed as a new procedure for the development of scales to measure marketing constructs. C-OAR-SE is based on content validity, established by expert agreement after pre-interviews with target raters. In C-OAR-SE, constructs are defined in terms of Object, Attribute, and Rater Entity. The Object classification and Attribute classification steps in C-OAR-SE produce a framework (six types of scales) indicating when to use single-item vs. multiple-item scales and, for multiple-item scales, when to use an index of essential items rather than selecting unidimensional items with a high coefficient alpha. The Rater Entity type largely determines reliability, which is a precision-of-score estimate for a particular application of the scale.

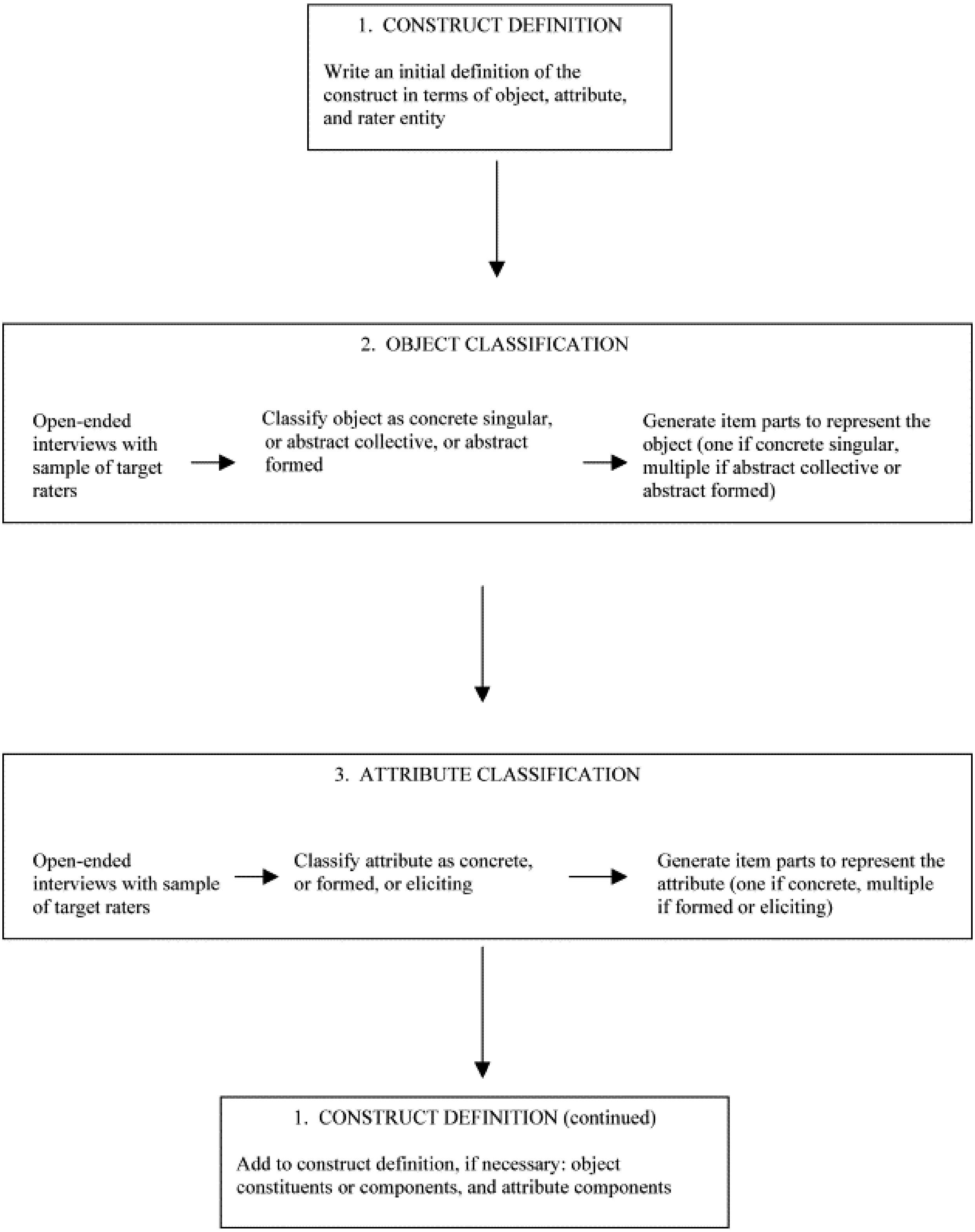
Keywords: Construct definition; Validity of measures; Multiple-item indexes; Multiple-item scales; Single-item scales; Reliability of scores

1. Introduction

This article proposes a new procedure for scale development—that is, the generation and selection of items to form a scale to measure a construct. It is illustrated here for constructs commonly used in marketing, although it is applicable within any of the social sciences. The new procedure is acronymically summarized as C-OAR-SE:[1] Construct definition, Object classification, Attribute classification, Rater identification, Scale formation, and Enumeration and reporting. These are the six steps needed to develop a proper measure of any construct. The C-OAR-SE procedure draws, in part, on the previous work of McGuire (1989) on the conceptualization of constructs, and Blalock (1964), Bollen and Lennox (1991), Cohen, Cohen, Teresi, Marchi, and Velez (1990), Edwards and Bagozzi (2000), Fornell and Bookstein (1982), and Law and Wong (1999), among others, on attribute classification. The total procedure, though, is new.

A new scale development procedure is needed in marketing. Traditionally, the development of marketing scales has followed the specific procedure advocated by Churchill (1979) but, in the present article, the traditional procedure is shown to be only a subset (one cell of six cells) of the C-OAR-SE procedure. Almost universal use of the traditional procedure, with its strict emphasis on factor analysis and internal-consistency reliability (coefficient alpha), which in recent years has been encouraged by structural equations modeling Bagozzi, 1994, Cohen et al., 1990 and Steenkamp & van Trijp, 1991, has led to some anomalous results in scale development in marketing. These include the deletion of conceptually necessary items in the pursuit of factorial unidimensionality (e.g., in SERVQUAL, Parasuraman, Zeithaml, & Berry, 1988, and in the Market Orientation scale, Narver & Slater, 1990), the addition of unnecessary and often conceptually inappropriate items to obtain a high alpha (e.g., in Taylor & Baker's, 1994 measure, and many others' measures, of purchase intention), and the use of high alphas as the solitary evidence for scale validity (slightly more than one in 10 of the scales in Bearden, Netemeyer, & Mobley's, 1993, well-known *Handbook of Marketing Scales* do this, and the practice is commonplace for invented scales in journal articles). Examples of such problems in widely used scales will be given, together with the scaling alternatives that C-OAR-SE would recommend in their place.

The article is structured in two parts. In the first and main part, the six steps of C-OAR-SE (see Fig. 1) are defined and the procedure for each step is explained, with examples. The second part addresses convention and shows why construct validity and predictive validity are inappropriate for scale evaluation, and why reliability should be regarded only as a precision-of-score estimate for a particular application.



1. CONSTRUCT DEFINITION

Write an initial definition of the construct in terms of object, attribute, and rater entity

2. OBJECT CLASSIFICATION

Open-ended interviews with sample of target raters

Classify object as concrete singular, or abstract collective, or abstract formed

Generate item parts to represent the object (one if concrete singular, multiple if abstract collective or abstract formed)

3. ATTRIBUTE CLASSIFICATION

Open-ended interviews with sample of target raters

Classify attribute as concrete, or formed, or eliciting

Generate item parts to represent the attribute (one if concrete, multiple if formed or eliciting)

1. CONSTRUCT DEFINITION (continued)

Add to construct definition, if necessary: object constituents or components, and attribute components

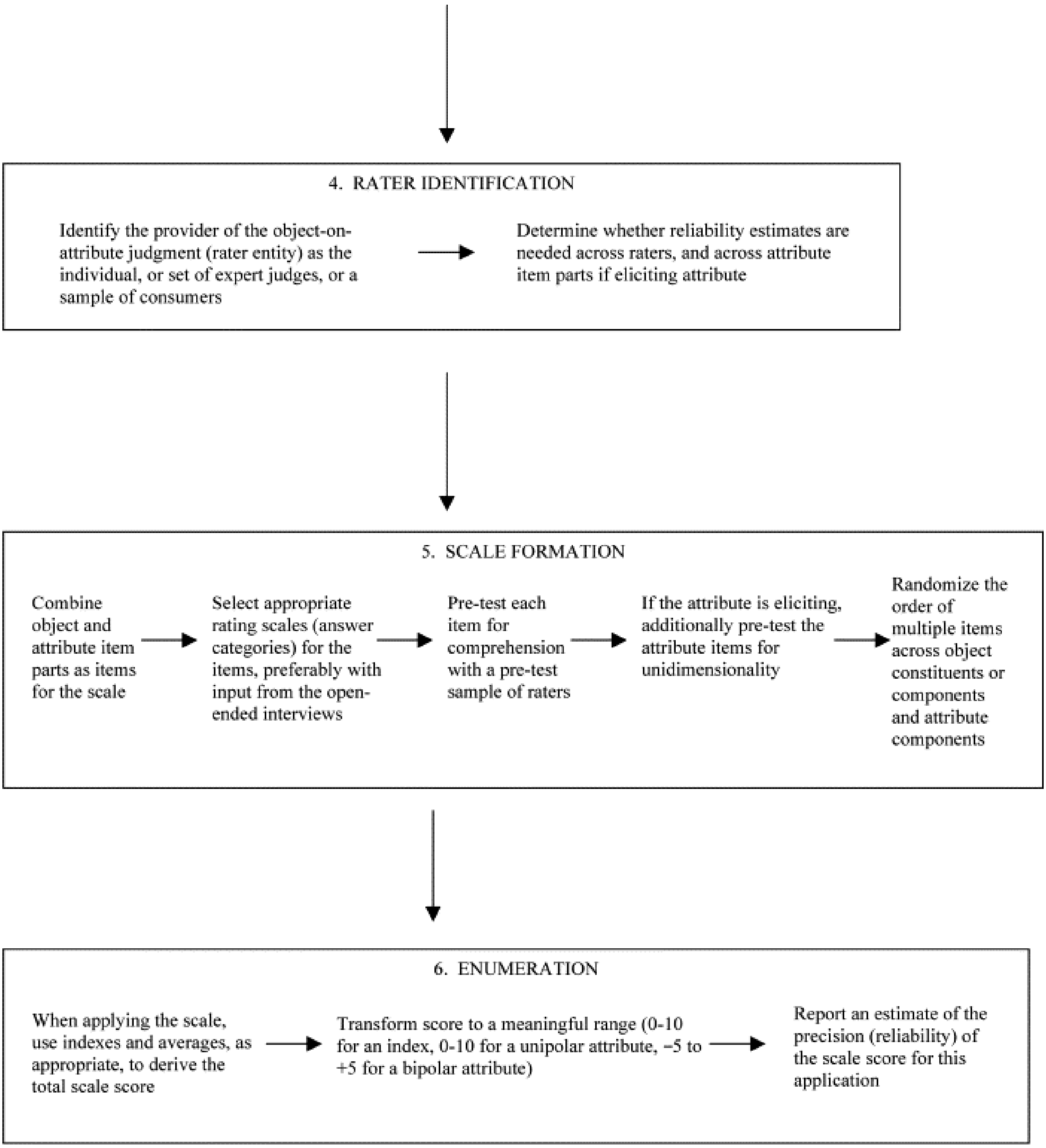

4. RATER IDENTIFICATION
Identify the provider of the object-on-attribute judgment (rater entity) as the individual, or set of expert judges, or a sample of consumers
Determine whether reliability estimates are needed across raters, and across attribute item parts if eliciting attribute
5. SCALE FORMATION
Combine object and attribute item parts as items for the scale
Select appropriate rating scales (answer categories) for the items, preferably with input from the open-ended interviews
Pre-test each item for comprehension with a pre-test sample of raters
If the attribute is eliciting, additionally pre-test the attribute items for unidimensionality
Randomize the order of multiple items across object constituents or components and attribute components
6. ENUMERATION
When applying the scale, use indexes and averages, as appropriate, to derive the total scale score
Transform score to a meaningful range (0-10 for an index, 0-10 for a unipolar attribute, −5 to +5 for a bipolar attribute)
Report an estimate of the precision (reliability) of the scale score for this application

Fig. 1. Steps in the C–OAR–SE procedure.

It should be made clear at the outset that the C-OAR-SE procedure is grounded in rationalism rather than empiricism (Wierenga & van Bruggen, 2000, pp. 72–77). There is no empirical test—beyond expert agreement—that can prove that C-OAR-SE produces scales that are more valid than those produced by the traditional procedure. As explained in the enumeration step of C-OAR-SE, this is because the typical tests of construct validity, notably multitrait–multimethod (MTMM) analysis, and reliability, notably factor analysis and coefficient alpha computation, all presume the theory underlying the traditional procedure, namely domain sampling theory, to be the true state of nature. Nor is predictive validity an appropriate test, because maximizing prediction usually reduces the validity of the measure. C-OAR-SE instead relies on logical arguments, and the concurrence of experts, based usually on open-ended input from pre-interviews with raters.

In C-OAR-SE, there is only one type of validity that is essential: content validity. Content validity is an "appeal to reason," conducted *before* the scale is developed, that the items will properly represent the construct (Nunnally, 1978,[2] p. 93). Content validity should not be confused with "face" validity (for instance, Bearden et al., 1993 equate the two in their *Handbook*, p. 3). Face validity is a post hoc claim that the items in the scale measure the construct (Nunnally, 1978, p. 111) and it is inadequate because you only see the items that were included and have to infer what may have been omitted and why. In C-OAR-SE, it is impossible to assert content validation, let alone face validation, without first having a comprehensive definition of what the "construct" is. C-OAR-SE provides the framework—the OAR framework—for construct definition.

2. C-OAR-SE: theory

2.1. Construct definition

A *construct* is "a conceptual term used to describe a phenomenon of theoretical interest" (Edwards & Bagozzi, 2000, pp. 156–157).[3] C-OAR-SE theory requires that constructs be conceptually defined (described) in terms of (1) the object, including its constituents or components, (2) the attribute, including its components, and (3) the rater entity. Failing this, the conceptual definition of the construct will be inadequate for indicating how the construct should be (operationally) measured. Following a framework suggested in McGuire (1989), all constructs can be conceptualized in terms of a focal object (hereafter called "object," be it physical or perceptual) and a dimension of judgment (or "attribute"); to these C-OAR-SE adds a third term, the judges or rater(s) (or "rater entity"). (In the notation introduced in the present article, *objects*, *attributes*, and *rater entities* will be written in capitals. An initial capital will be used to denote *constituents* and *components* of objects and components of attributes. Scale *items* will be written in quotation marks.) In the eyes of many, SERVICE QUALITY would be a construct, but C-OAR-SE sees this only as an attribute. One cannot conceive of SERVICE QUALITY in the abstract; it has to have a focal object, such as SERVICE QUALITY IN AMERICA, or IBM's SERVICE QUALITY. Furthermore, according to C-OAR-SE, the construct has to specify a rater entity. IBM's SERVICE QUALITY AS PERCEIVED BY IBM's MANAGERS is a different "phenomenon of theoretical interest" than IBM's SERVICE QUALITY AS PERCEIVED BY INDUSTRY EXPERTS, or IBM's SERVICE QUALITY AS PERCEIVED BY CUSTOMERS. To give another example, in measuring ostensibly the "same" construct of the COMPANY's MARKET ORIENTATION, Kohli, Jaworski, and Kumar (1993) used as rater entities SENIOR MARKETING EXECUTIVES and separately SENIOR NON-MARKETING EXECUTIVES, Slater and Narver (1994) used SBU MANAGEMENT TEAMS, and Sigauw, Brown, and Widing (1994) used SALESPEOPLE. With the different rater entities' perspectives, these constructs are *not* the same and should not be so loosely described. The conceptual definition of the construct should specify the object, the attribute, and the rater entity.

There are some examples of conceptual definitions of constructs in marketing that do follow this O-A-R structure but most do not. The contrast is seen in a pair of examples. Zaichkowsky (1994) defined INVOLVEMENT, the construct for her PERSONAL INVOLVEMENT INVENTORY, as "[a] person's perceived relevance of the advertisement" (p. 61). This definition is basically adequate because it specifies the object, the ADVERTISEMENT, the attribute, PERSONAL RELEVANCE, and the rater, a PERSON, that is, a consumer. PERSONAL RELEVANCE, though, is conceptualized by that author as a complex attribute comprising a Cognitive component and an Affective component, in which case its components should be included in the definition. Also, note that alternative perspectives could be specified for the rater, such as that of the CREATIVE TEAM who produced the advertisement in the first place, which is the only perspective provided on an ad's "relevance" when the ad is recommended to the client without consumer pre-testing. Schlinger (1979), on the other hand, defined the construct underlying the VIEWER RESPONSE PROFILE as “affective reactions to advertisements” (p. 37). This is not a satisfactory conceptual definition, because, firstly, the object is actually a single ADVERTISEMENT at a time, not ADVERTISING in general; secondly, AFFECTIVE REACTIONS is an attribute but does not describe what is actually measured (the VRP includes not only affective reactions but also cognitive reactions such as “The commercial was very realistic—that is, true to life”); and, thirdly, the rater entity is not specified, though presumably it would be VIEWERS of the advertisement, that is, a consumer sample.

The basic set of questions to be answered when writing the conceptual definition of a construct, therefore, is: What is the object and does it have constituents or components? What is the attribute and does it have components? Who is the rater entity? (A glossary of technical terms used in C-OAR-SE is provided in Table 1.) A complete conceptual definition of the construct then allows the remaining five steps in the C-OAR-SE procedure to be implemented to develop the measurement scale. In practice, as shown in Fig. 1 earlier, an initial definition is made in terms of object, attribute, and rater entity, and then steps 2 and 3 need to be carried out to arrive at a complete definition that includes, when necessary, object constituents or components, and attribute components.

Table 1. C-OAR-SE glossary of terms

Constructs
Construct definition: A phenomenon of theoretical interest described in terms of (1) the object, including its constituents or components, (2) the attribute, including its components, and (3) the rater entity.
Object: Focal object being rated.
Constituents: Sub-objects that form the parts of an abstract collective object, denoting what the object includes.
Components: Parts of an abstract formed object, a formed attribute, or an eliciting attribute,

comprising what the object or attribute means, denotatively, to raters.
Attribute: Dimension of judgment.
Rater entity: The judges or rater(s).
Types of objects
Concrete: Nearly everyone (of a sample of raters) describes the object identically.
Abstract: The object suggests somewhat different things to the sample of raters. These different things will be the constituents or the components.
Concrete singular object: Concrete, with only one object to be rated (e.g., COKE).
Abstract collective object: Set of concrete singular objects that collectively form a higher-level category in the opinion of experts (e.g., SOFT DRINKS). The superordinate category object is abstract but its sub-objects are concrete singular objects for the rater(s).
Abstract formed object: Object that suggests somewhat different things to the sample of raters (e.g., MARKETING, as perceived by the GENERAL PUBLIC). These different things will be the components (e.g., Selling, Advertising, Promotional events). Components must be concrete singular objects (e.g., Advertising is regarded by this rater entity as concrete singular). Experts decide main defining components to be included in the measure of the abstract formed object.
Types of attributes
Concrete: Nearly everyone (of a sample of raters) describes the attribute identically.
Abstract: The attribute suggests somewhat different things to the sample of raters. These different things will be the components.
Formed: (Abstract) attribute in which the main components add to form the attribute (e.g., SOCIAL CLASS). The components must be concrete (e.g., Occupational prestige, Education

level, Income, Area-of-residence prestige). All main components must be included in the scale (definitive items).
Second-order formed attribute: Very abstract formed attribute that has formed attributes as components (e.g., MARKET ORIENTATION). All main second-order components (e.g., Customer orientation, Competitor orientation, Interfunctional coordination, Long-term focus, Profitability) and all main first-order components (e.g., Understanding customer needs, Measuring customer satisfaction), the latter concrete, must be included in the scale.
Eliciting: (Abstract) attribute that is an internal trait or state that has outward manifestations, which are mental or physical activities, as components (e.g., INNOVATIVENESS). The components must be concrete (e.g., Being the first to try new products, Not relying on others for opinions, Taking chances). A sample of components is sufficient (indicator items). They must be shown to be unidimensional by a coefficient β(Revelle, 1979) of approximately 0.7 and internally consistent by a coefficient α of approximately 0.8.
Second-order eliciting attribute: Very abstract eliciting attribute that has eliciting attributes as components (e.g., INVOLVEMENT). All main second-order components must be included in the scale (e.g., Cognitive involvement, Affective involvement) and these in turn each has a sample of outward manifestations as components. Recommended β=0.7 and α=0.8 for each of the eliciting attributes as second-order components and β=0.5 and α=0.7 for the combined scale.
Types of rater entities
Individual rater: Self, as in self-rating of a personal attribute when the object is oneself.
Group raters: Sample of consumers, industrial buyers, managers, salespersons, or employees. Most often used to rate an external object (not oneself) on an attribute.
Expert raters: Small group of judges with expertise regarding the construct. Used to rate any

external object (including other individuals) on an attribute. Also used in the C-OAR-SE procedure to make final selection of (ratify) constituents or components, from ratings by a sample of individual raters or group raters, and to rate content saturation of items for an eliciting attribute.
Scale formation
General: Putting together object item parts with attribute item parts to form scale items. For multiple-item scales, randomize items over both the object and the attribute.
Item stem: The “question” part of an item.
Item leaves: The “answer” alternatives for an item.
Enumeration
General: The rule for deriving a score from the scale.
Single-item score: The rating from a single-item scale in which a concrete singular object is rated on a concrete attribute.
Index: Multi-item score over items for an abstract collective object, abstract formed object, or formed attribute. Sum, sometimes with constituent or component scores weighted; or profile, usually with conjunctive cutpoints on the component scores.
Eliciting attribute scale average: Multi-item mean score across attribute items in a scale for measuring an eliciting attribute. Sometimes the mean of multiplied scores, if pairs of components are multiplicative.
Note also double indexes, and averages which are then indexed (see the six cells of C-OAR-SE in Table 3).
Validity
Content validity: *A priori* evidence that the items are a good representation of the construct

(from expert judges). Content validity established per the C-OAR-SE procedure is sufficient for use of the scale.
Face validity: *Post hoc* evidence of content validity. Inadequate because of omitted-items bias.
Construct validity: In C-OAR-SE, construct validity is content validity, properly established. Multitrait–multimethod (MTMM) evidence of construct validity is inconclusive and therefore irrelevant.
Predictive validity: Dependent on previously established content validity. A close approximation of the population correlation between the scale and the criterion is needed, not a maximized correlation.
Nomological validity: Multivariate extension of predictive validity in which population partial correlations should be approximated for the scale.
Reliability
Reliability: A precision-of-score estimate for a particular application of the scale. Estimation formula depends on the attribute type and the rater entity type (see Table 4).

2.2. Object classification

The object part of the construct can be singular, collective of constituents, or have multiple components. However, there is another dimension involved here, namely concrete-abstract. The alternative object classifications are: concrete singular, abstract collective, and abstract formed.

2.2.1. Concrete singular object

Concrete singular objects represent the case that is usually assumed in the traditional scale development procedure. It is assumed that virtually all raters know what the object is and that, for them, there is only one object. For instance, in rating IBM's SERVICE QUALITY, it is assumed that the object, IBM, is described similarly by all raters (which makes it concrete) and that it is singular (that is, a single overall company, rather than, say, a set of geographic divisions or departmental divisions). In applying C-OAR-SE, a group of expert judges is used to ratify the classification of the object. Their judgments, for other than simple cases, are best preceded by open-ended interviews with a sample of target raters (see Schwarz, 1999, and see Deshpandé & Zaltman, 1984, for an excellent application). If the group of experts agree that the object is indeed concrete singular, then only one item (or, strictly speaking, one *item part*, because there is still the attribute part of the item to be decided) will be needed to represent the object. IBM, for example, would be represented by only one item part: "IBM."

There is another type of object that also would be classified as concrete singular. This is when the object is not a single object but is singular in the sense that it is a set of reasonably homogeneous objects. The object COCA-COLA (the drink), for instance, includes canned, bottled, and soda fountain forms, as well as different sizes of each, but the construct CONSUMERS' EVALUATION OF COKE, for instance, would assume that the object, COKE, is homogeneous, and thus concrete singular. Naturally, the researcher might have a more specific purpose, such as to gauge consumer evaluations of a new container type or size of Coca-Cola, in which case the specific object would be defined accordingly and would be concrete singular.

2.2.2. Abstract collective object

Abstract collective objects are objects that are heterogeneous in the eyes of the raters, that is, they are seen as separate constituents, but form a set at a *higher categorical level* in the eyes of the researcher. CARBONATED SOFT DRINKS would be an example. The advisable procedure would be to identify the main types of carbonated soft drinks, such as COLAS, NON-COLAS, and CARBONATED MINERAL WATER, for the purpose of CONSUMERS' ratings, with an item (again, an item part) for each of these constituents. Thereafter, the RESEARCHER will aggregate the ratings. For example, if the attribute of interest is LIKING, by CONSUMERS as the rater entity, then three items would be needed: COLA LIKING, NON-COLA LIKING, and CARBONATED MINERAL WATER LIKING. Ratings on these three items would form an *index* scale, summed across objects, of consumers' liking of CARBONATED SOFT

DRINKS. The researcher might decide to weight the ratings by the relative consumption incidence of the three objects in the collective set. Note that the unidimensionality of the object scale and its internal consistency are not relevant. What counts is *content*; that is, whether the items (again, item parts) are a valid constitution (are representative constituents) of the abstract collective object.

An important application of the abstract collective object classification is to the constructs that produce treatments (manipulations) in *experiments*. Experimental treatments usually are represented by just one object item. For instance, when investigating the effect of FEAR APPEALS, the fear treatment (more correctly, the threat treatment) may be represented by just one ad. This ad is a sample from a larger collection (population) of such ads and, no matter how large the sample size of participants, the effective sample size of the object is n=1. Journal reviewers are quite familiar with this problem but it is not widely recognized by researchers (Wells & Windschitl, 1999). The issue is one of stimulus generalizability and this becomes clear by realizing that an experimental treatment is measuring a construct. In the example above, the object is FEAR (THREAT) ADS, the attribute is FEAR, and the rater entity is the INDIVIDUAL (self-ratings by the experimental participants). The object of the construct is an *abstract collective object*. Defining the construct thoroughly with the O-A-R framework helps to make more obvious that an experimental manipulation using one object from the collection is relying on that object being a highly typical exemplar of the collection because it is, in effect, a single-item measure of the experimental treatment. A multiple-item sample of representative constituents (a range of fear ads) would provide safer generalization of the results.

2.2.3. Abstract formed object

Abstract formed objects arise when people's interpretations of the object differ, that is, they see the object as having *different components*. Objects are noun concepts that create “chunks of perceptual experience” (Medin, Lynch, & Solomon, 2000, p. 125). For abstract objects, this experience is relatively heterogeneous across people (raters). CAPITALISM would be an example. Some might associate it strongly with a component such as Free enterprise, others with Profit-seeking, and still others with Material acquisition.

Expert judges must ratify the *main components* of CAPITALISM, assisted by open-ended interviews with target raters, and write an item part for each component.

An abstract formed object is not simply a collection of concrete objects and therefore it is not abstract collective. An abstract *formed* object has components, whereas an abstract *collective* object has constituents. An abstract formed object's item parts must answer the question, “What does it mean?,” whereas an abstract collective object's item parts must answer the usually easier question, “What does it include?”

If abstract formed objects have components, then it follows that objects, and not just attributes, can be “multicomponential,” which is a perspective not widely recognized in the marketing literature.[4] The components of an abstract formed object do not have to be unidimensional with regard to the attribute on which they are to be rated. Indeed, in the CAPITALISM example, raters might endorse *some* components of CAPITALISM but not others. This means that the pursuit of a “high alpha” across item parts is precisely the wrong way to go, because it would result in the deletion of items that form part of the definition of the object. Instead, the component items form an index.

In buyer behavior research, the constructs known as VALUES are an important example of abstract formed objects that are typically “undermeasured,” producing results of doubtful validity. Most often, VALUES have been measured using the Rokeach Value Survey, RVS (Rokeach, 1973), or the popular abbreviated version, the List of Values, LOV (Kahle, 1983). The attribute is usually IMPORTANCE IN MY DAILY LIFE and the rater is the INDIVIDUAL. The RVS and the LOV scales, quite incredibly, employ just one item to represent the complex object of a VALUE. The RVS does provide a brief explanation of each object (e.g., “PLEASURE…an enjoyable, leisurely life”; “A SENSE OF ACCOMPLISHMENT…lasting contribution”) but raters do not rate any components, just the overall object. The LOV just uses a single word or phrase, without explanation, and with no component ratings. Qualitative research using open-ended discussion with consumers from different cultures suggests that the varying interpretations of these brief descriptions of VALUES, as objects for rating, make the results from single-item measures virtually meaningless (Chan, 2001). C-OAR-SE would insist on multiple items, representing the components of the VALUE, which would greatly mitigate the problem.[5]

To summarize: Object classification, the second step in the C-OAR-SE scale development procedure, involves a group of experts, usually assisted by open-ended interviews with target raters, classifying the object of the construct as either *concrete singular* (which will then require just a single-item part), *abstract* collective (multiple-item parts identifying the main constituents), or *abstract formed* (multiple-item parts identifying the main components that make up the object's meaning). The latter two classifications mean, when it comes to Enumeration and reporting, which is the last step in C-OAR-SE, that the object item parts will require an index.

2.3. Attribute classification

The third step in C-OAR-SE is to classify the attribute in the construct, which is the dimension on which the object is being judged. Attribute classification is usually the most difficult step in C-OAR-SE because the classification of some attributes, such as the widely used attribute, ATTITUDE, as explained later, can differ depending on the construct's role in the broader theory or model of which the construct is a member. Also, attribute classification has the most radical implications for the way scales should be developed in marketing. The three alternative attribute classifications are: concrete (singular), (abstract) formed, and (abstract) eliciting. The parenthesized terms are accurate but redundant for attribute classifications, so the brief terms concrete, formed, and eliciting will be used.

2.3.1. Concrete attribute

Many of the attributes that we measure in marketing are concrete. As with a concrete singular object, a *concrete attribute* has virtually unanimous agreement by raters as to what it is, and they clearly understand that there is only one, or holistically one, characteristic being referred to when the attribute is posed, as in a questionnaire or interview, in the context of the to-be-rated object. Examples would be LIKABILITY (e.g., of an advertisement), QUALITY of a *familiar or easy-to-judge* object (e.g., of a branded product or service), PRICE PERCEPTION (e.g., “inexpensive…expensive”), and BUYING INTENTION.

When an attribute is judged to be concrete, there is no need to use more than a single item (part) to measure it in the scale. Drolet and Morrison (2001) show that the now almost standard practice of attempting to measure a concrete attribute by inserting multiple items to “capture” it (and to satisfy journal requirements for multi-item measures) not only leads to wasteful redundancy, but the additional items usually “drift off” the original conceptually defined attribute and start picking up the substance of *other* attributes. The problem here is not that the additional items help to reduce “random error,” as if respondents are not sure what they are responding to, as implied by the oft-heard view that “single items are unreliable” (e.g., Churchill, 1979 and Nunnally, 1978). Rather, it is a validity problem. This loss of validity is untenable and cannot be offset by appealing to a high alpha. Take the example of a three-item measure of BUYING INTENTION used in a study by Taylor and Baker (1994), which is quite typical (answer scales omitted for the present purpose):

(1) The next time I need the services of a _____, I will choose XYZ.
(2) If I had needed the services of a _____ during the past year, I would have selected XYZ.
(3) In the next year, if I need the services of a _____, I will select XYZ.

Consumer responses to these items are highly correlated, as might be expected, and produce a high alpha of over 0.90. However, why the need for multiple items here? What were the researchers interested in measuring? Item 1 refers to IMMEDIATE INTENTION. Item 2 refers to PAST INTENTION. Item 3 refers to FUTURE INTENTION. These are different questions (managerially anyway). Here, high reliability (internal consistency) is meaningless and combining the items produces *lower* validity. If the researchers were simply interested in measuring BUYING INTENTION, then surely the first item alone was sufficient. As practitioners have long demonstrated (e.g., Rossiter & Eagleson, 1994 and Urban & Hauser, 1993), for measuring concrete attributes such as AD LIKABILITY or PURCHASE INTENT, single-item measures are definitely valid. This, of course, presumes that an accurate description of the attribute is selected for the “stem” of the rating question and that the “leaves” (the response categories) are similarly clear, concrete and, unless nominal, are psychologically equal interval (see Section 2.5.2).

2.3.2. Formed attribute

Another attribute type consists of those that are abstract (raters' answers differ moderately if asked what the characteristic is) and formed (the main things that it refers to, its components, add up to what the attribute means). *Formed attributes* are complex and multicomponential, and the important realization is that responses to the components cause the attribute, that is, they “make the attribute appear.” Other measurement theorists Bagozzi, 1994, Blalock, 1964, Bollen & Lennox, 1991, Diamantopoulos & Winklhofer, 2001, Fornell & Bookstein, 1982 and Law & Wong, 1999 have also identified this type of attribute. The term “formed attribute” is preferred to “formative attribute.”[6] The term “composite attribute” has the right connotation but is deficient insofar as all multiple-item attribute scores are necessarily composites. Also, these previous writers refer to the entire construct as formative, rather than, as here, to just the attribute. In C-OAR-SE, the attribute part of the construct can be formed but the object part can be any of the classifications of concrete singular, abstract collective, or abstract formed.

An example of an attribute that can be a formed attribute is SERVICE QUALITY. From one rating viewpoint, adopted for familiar or simple services, SERVICE QUALITY is concrete. From another rating viewpoint, whenever the rater has to “think about it” before answering, SERVICE QUALITY is the sum total of a number of specific activities (ratings of these) that make up the overall performance of a particular industry's service. They are what might be called *proximal antecedents* as distinct from more remote causes.[7] If the experts decide that the target raters are likely to make this summative type of judgment, then SERVICE QUALITY is a formed attribute.

For a formed attribute, the components that make it up have a number of properties. First, the components themselves are attributes; they are subsidiary attributes of the focal attribute. SERVICE QUALITY is actually a *second-order* formed attribute in that its components (Reliability, Assurance, etc.) are *also* formed attributes. The components of these components, that is, the first-order components, must be concrete, otherwise they cannot be rated consistently (e.g., "On-time delivery" might be a first-order component of Reliability). The goal is to develop one good item for each first-order component. The reasons for this are exactly the same as for using a single item to measure a concrete attribute. Second, the formed attribute need only include its main components rather than every possible component and this calls for expert judgment aided by a reasonable cutoff for inclusion (the aim of using a *census* of components is not practically possible, contrary to the advice of Bollen & Lennox, 1991, and Diamantopoulos & Winklhofer, 2001, because it would lead to an infinite search for low-incidence components that most raters would not include in the attribute concept). Suppose that 20 target raters are interviewed in an open-ended manner about the attribute so that its components are identified. Expert judgment is needed to categorize distinct components and then a reasonable rule of mention of the component by, say, at least one-third of the interviewees can be applied to select "main components." No sort of ratings and factor analysis should be used, because the "perceived dimensionality" of the components is not relevant; all that is needed is a set of distinct components as decided by expert judgment. Third, once decided, these main components must *all* be present in the scale because the items representing them are the *defining items* for the attribute. In other words, a formed attribute does not follow the domain *sampling* model. This means that items are *not* interchangeable, that is, items cannot be added or deleted from the scale. Item selection to increase the "reliability" of the formed scale is definitely not appropriate. Fourth, the formed attribute scale will not be unidimensional (because the focal attribute is not) and thus factorial unity in factor analysis and internal consistency, as indicated by coefficient alpha, are not relevant (the components, and thus the item scores, are likely to be positively correlated but not *highly* correlated and the researcher should not try to achieve this). The scale items simply form an index obtained by combining the item scores. These points have been made several times over the last 35 years (see Bollen & Lennox, 1991 and Diamantopoulos & Winklhofer, 2001; and especially Bagozzi, 1994) but the theory supporting formed attributes has not been very clear and the most unfortunate result has been that few have correctly identified this attribute type.

There are many examples of marketing constructs whose attribute is a formed attribute but which, due to the emphasis in traditional scale development on factor analysis and alpha, have attribute scales that are wrongly constituted. These include among the classic scales, as should now be evident, SERVQUAL (Parasuraman et al., 1988; see also Mittal & Lassar, 1996 and Smith, 1999), MARKET ORIENTATION (Narver & Slater, 1990), CUSTOMER ORIENTATION (Saxe & Weitz, 1982), and the VIEWER RESPONSE PROFILE (Schlinger, 1979). All these attributes should have had their main components agreed on (often this was done originally but then empirically altered by factor analysis), should have had one good item per first-order component chosen (not done), and the item scores summed as an index (not done). New scales often make the same errors, as a careful check of recent issues of the best marketing journals readily reveals. Even Diamantopoulos and Winklhofer (2001), who strongly advocate the use of index measures for certain attributes, although their decision rule for attribute classification is not very clear, make the error of using statistical analysis to delete items from formed-attribute scales. On the other hand, an excellent example of the right procedure for developing index items for attributes can be found in the well-known study about marketing managers' use of market research, by Deshpandé and Zaltman (1984). The choice between—the classification of—formed and eliciting attributes, the latter described below, is critically important. There is little doubt that Deshpandé and Zaltman's model and conclusions would be quite different had they used the conventional item-selection procedure, which assumes that all attributes are of the eliciting type. Law and Wong (1999) provide another example in which JOB CHARACTERISTICS (AS PERCEIVED BY EMPLOYEES) and LIKING OF SUPERVISOR are significant causes of JOB SATISFACTION when all three constructs' attributes are measured in the conventional factor-analytic, item-deletion manner. However, when all three constructs' attributes are measured as formed attributes, which is correct according to C-OAR-SE, then only JOB CHARACTERISTICS is a significant cause.

The theoretical and practical implications of the attribute classification decision are major, as indeed they are in general for construct definition.[8] Bagozzi (1994, p. 334) says that formative indicators (formed attributes) are only "occasionally useful" in marketing measures. To the contrary, formed attributes are probably the prevalent type in marketing constructs.

2.3.3. Eliciting attribute

There is a third type of attribute in some marketing constructs that can be called an *eliciting* attribute. In this third type, the attribute is abstract (raters' answers would differ moderately if asked what the characteristic is) but in this case, the attribute is an "internal" trait or state (a disposition). This type of attribute, according to its theoretical function, *causes* the responses to its measurement items (hence the attribute is "eliciting").[9] The items are *indicative manifestations* of the trait or state.

Note that SERVICE QUALITY, for example, is *not* of this type: there is not something "in" the brand of service that "causes" Reliability, Assurance, Tangibles and other componential responses. Rather, it is the other way round: *they* cause the judgment of overall service quality, and that attribute is therefore a formed attribute. In contrast, it could be reasoned that SERVICE *EMPHASIS*, as company policy, a vendor trait, is an eliciting attribute: *it* causes the performance of a host of service activities.

Relatively few marketing constructs have attributes that are eliciting, yet the traditional scale development procedure assumes that all attributes are of this type. All constructs that have an eliciting attribute are *traits*, such as NEED FOR COGNITION (Cacioppo & Petty, 1982) and STYLE OF PROCESSING (Childers, Houston, & Heckler, 1985), or else are shorter-term *states*, such as PERCEIVED EFFICACY (Rogers, 1975) and PERSONAL INVOLVEMENT (Zaichkowsky, 1994). The theorists who developed the scales for these constructs posited them as internal dispositions that cause the responses to the items. However, perhaps due to the tendency to anthropomorphize companies and brands as having "personalities," it is all too easy to fall into a trait-like interpretation of nontrait attributes. Two notable examples are MARKET ORIENTATION (Narver & Slater, 1990) and CUSTOMER ORIENTATION (Saxe & Weitz, 1982). In neither case did the authors define these attributes as traits. Rather, they were conceptualized as a *set of activities* that compose the attribute (see Narver & Slater, 1990 and Saxe & Weitz, 1982). As defined, these are formed attributes, not eliciting attributes, and the unnecessary use of factor analysis and coefficient alpha to select and delete items means that these scales are not as valid as they could be. Many other examples could have been singled out (marketers have vastly over-used the eliciting attribute assumption to develop scales, borrowed from individual-differences psychology). Really, these earlier scales should be redesigned, and certainly future scales must not make this error when the attribute is not of the eliciting type.

Eliciting attributes can be unidimensional in a first-order factorial manner, or they may have components (sometimes called facets) which are themselves unidimensional and are intercorrelated as a second-order factor; that is, the *component* scores are unidimensional when *they* are factor analyzed (Nunnally, 1978, pp. 431–432). Sometimes, a component is used alone as the attribute of theoretical interest; for example, QUANTITATIVE ABILITY (Lumsden, 1957). In other cases, a more complex eliciting attribute is of interest; for example, GENERAL MENTAL ABILITY, of which Quantitative ability is a component, with the other main component being Verbal ability. The components are elicited mainly by a unidimensional second-order factor (Spearman's, 1904*G* factor). An example of a componential eliciting attribute in marketing is PERSONAL INVOLVEMENT (Cognitive involvement and Affective involvement as components; Zaichkowsky, 1994). Second-order eliciting attributes are not common in marketing. For example, STYLE OF PROCESSING (Verbal style and Visual style as components; Childers et al., 1985) does not qualify, because STYLE is *not* a second-order eliciting common cause. Rather, VERBAL STYLE and VISUAL STYLE are independent eliciting (trait) attributes. Nor does PAD (Mehrabian & Russell, 1974); its components of Pleasure, Arousal, and Dominance are *not* correlated (they are orthogonal). Its components are separate eliciting (state) attributes, PLEASURE, AROUSAL, and DOMINANCE.

Items to measure eliciting attributes should be written as a set of distinct *activities*, mental or physical, that, as items, are concrete. Particularly to be warned against is the tendency for academic marketing researchers simply to generate, as items, synonyms of the main verb, for example, “I enjoy thinking,” “I like thinking,” “I prefer thinking,” or synonyms of the main adjective, for example, “Thinking is enjoyable,” “Thinking is pleasant,” “Thinking is preferable.” The multiple-adjectives criticism may be made, for example, of Zaichkowsky's PERSONAL INVOLVEMENT scale, with its two components of Cognitive involvement and Affective involvement. Use of synonyms is not a valid substitute for developing items that refer to related but distinct activities. Paraphrases were certainly not what scale development pioneers such as Thurstone and Likert had in mind and this approach should not be used today. The right approach is illustrated by the NEED FOR COGNITION scale, where the items represent distinct, mainly mental, activities, such as "I really enjoy a task that involves coming up with new solutions to problems," "I usually end up deliberating about issues even when they do not affect me personally," and "I prefer watching educational to entertainment programs" (Cacioppo & Petty, 1982, pp. 120–121). The items may alternatively be physical activities, as are most of the items measuring OPINION LEADERSHIP, which King and Summers (1970) conceptualized as a consumer trait ("Talking about," "Giving information," "Being asked," are some of the physical activities in the scale).

For an eliciting attribute, the items represent its specific manifestations—its *proximal consequences*. Because there are many of these, and more than enough to "capture" the trait and be sure what is being measured, the items are interchangeable to the extent that a reasonable *sample* of the items will do, as domain sampling theory is appropriate for this one type of attribute. The items for an eliciting attribute are thus *indicative* rather than defining as for a formed attribute. Moreover, since it is one trait that should be causing responses to the items (Lumsden, 1961), it is necessary to demonstrate that the item scores are *unidimensional*. There must be enough items to make sure the attribute scale is sampling the trait adequately (Lumsden, 1978). Practically, this means three to five items overall, or per component if the eliciting attribute is second-order, but 30 or so items would be quite usual for clinical applications or educational or job entry tests, where very precise scores for individuals are required.

Pursuing the admirable goal of conciseness, Mowen (2000) has shown that eight fundamental personality traits, which extend the well-known "big five" traits, can be efficiently measured with just three to five, and typically four, carefully chosen manifestation-type items (see also Burisch, 1997 and Paunonen, 1984).[10] Coefficient alphas derived from his samples for these scales were about 0.8, which is ideal (much above that for a short scale, the items are likely to be redundant). Similarly, Steenkamp and Baumgartner (1995) have shown that a 7-item measure of CHANGE-SEEKING TENDENCY, which is rather like Mowen's (2000) NEED FOR AROUSAL, is better (similar high alpha and no social desirability bias) than the 95-item original scale and indications are that a 6-item scale (dropping their sixth item) would do as well. Contrast these efforts with the NEED FOR COGNITION scale, for instance, which has 34 items or, in a later version (Cacioppo, Petty, & Kao, 1984), 18 items, too many for survey research applications.[11] It is obviously important, if eliciting-attribute measures such as personality traits are going to be adopted by practitioners, that brief multiple-item scales be developed for them. Not only this, but "overmeasurement" of a construct can spuriously inflate its correlation with other constructs via what Feldman and Lynch (1988) term "self-generated validity."

One difficult construct that warrants discussion, because of its ubiquitous use in marketing and consumer research, is ATTITUDE. Depending on how it is conceptualized as a construct, always with an object and a rater entity, which we will not discuss here, the attribute, ATTITUDE, can be either formed, concrete, or eliciting (perhaps this is not surprising given its multiple roles in social science, including consumer behavior theory). ATTITUDE is usually defined as the rater's overall evaluation of an object (e.g., Calder & Ross, 1973 and Fishbein & Ajzen, 1975). If the researcher is studying attitude formation, in which there is *as yet* no overall attitude, then the ATTITUDE attribute is clearly a formed attribute—it is a composite of the various object beliefs or perceptions, and associated feelings or affect, that the rater experiences during attitude formation (see Bodur, Brinberg, & Coupey, 2000, for belief and affect compositional models of attitude, and Rossiter & Percy, 1997, p. 123). Once an attitude is learned and *established*, most theories of attitude functioning regard it as *concrete*—an "overall evaluation"—and thus measure it with a single-item rating scale. However, another influential line of attitude theory (e.g., Bagozzi & Burnkrant, 1979, Breckler & Wiggins, 1989, Edwards, 1990 and Millar & Millar, 1990; and see Ajzen, 2001) posits that objects almost always evoke thoughts and feelings separately (cognitive reactions and affective reactions) and that phenomenologically there is *not* an overall evaluation. In this dual-state view, the ATTITUDE attribute would be eliciting (a second-order eliciting attribute), with the Cognitive and Affective components *also* being eliciting. Note that unlike in the attitude formation situation, the two components' items, those measuring Cognitive attitude and those measuring Affective attitude, would be expected to be respectively unidimensional by factor analysis and the two components' scores moderately positively correlated for most attitude objects.

To summarize: The attribute part of the construct is the most complex to classify and undoubtedly requires experts' agreement. Attributes can be classified as concrete (requiring just a single-item part), formed (multiple-item parts identifying the main components, its proximal antecedents), or eliciting (multiple-item parts representing an adequate sample of its manifest proximal consequences). Attribute classification is the most difficult step in C-OAR-SE and often will be the largest determinant of the way the construct is measured. The discussion turns now to identification of the rater entity.

2.4. Rater identification

The fourth step in C-OAR-SE is the final part of the construct's definition, which is identification of the rater entity. Constructs differ depending on whose *perspective* they represent. Objects' ratings on attributes cannot be divorced from the perceiver (the rater). This was illustrated earlier with the example of IBM's SERVICE QUALITY as perceived, respectively, by MANAGERS, by INDUSTRY EXPERTS, or by CUSTOMERS. The rater entity is part of the construct.

There are three types of rater entity: individual, experts, and group (the last a potentially broad category including, in marketing, samples of consumers, buyers, managers, salespersons, and employees). These rater classifications are explained as follows.

The type of rater entity has fundamental implications for the way scale-score *reliability* is estimated. This will be taken up in Section 4.

2.4.1. Individual rater

One type of rater entity is the *individual*. The rater entity is the INDIVIDUAL for all individual-difference constructs that involve self-reports. Of course, individual differences may alternatively be rated by EXPERTS or by PEERS, who are a special type of group-rater entity. However, individual self-reports are the most prevalent type of rater entity for constructs in marketing (a meta-analysis by Peterson, 1997, of 259 studies in the major journals found that just over half of the scales employed in these studies were "respondent-centered," that is, they required respondents' self-ratings). For self-reports, the rater entity is the INDIVIDUAL, the object is the SELF (if a trait) or the EXTERNAL STIMULUS (if a state),[12] and the attribute is the INDIVIDUAL-DIFFERENCE DISPOSITION of interest.

Examples of constructs (here named by the attribute only) for which the rater type is the individual include, as previously discussed, INVOLVEMENT, ATTITUDE, OPINION LEADERSHIP, and NEED FOR COGNITION.

2.4.2. Expert raters

Some constructs require *expert raters*—trained judges—to perform the ratings. The expert raters are essentially conducting a *content analysis*, and thus reliability of the ratings depends on achieving high inter-judge agreement. (C-OAR-SE classification done by experts for purpose of content validation is content analysis.)

Expert ratings may be applied to ADS as the objects (e.g., Domzal & Kernan, 1993 and Rossiter, 1981), or to PRODUCTS as the objects (e.g., the product ratings in *Consumer Reports*). Expert ratings also can be applied to COMPANIES as the objects. For instance, Steinman, Deshpandé, and Farley (2000) measured EMPLOYEES' ratings of various companies' MARKET ORIENTATION and also CUSTOMERS' ratings, finding differences, and could have collected INDUSTRY EXPERTS' ratings to provide a more independent assessment.

2.4.3. Group raters

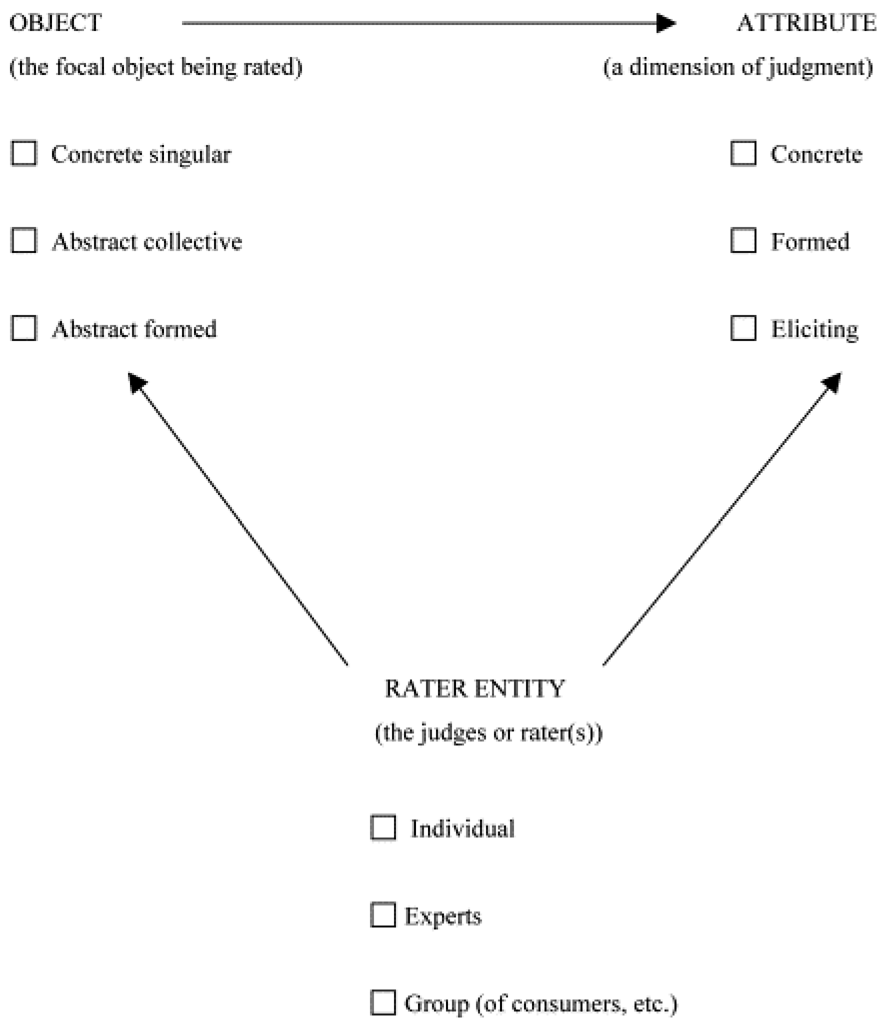
The third possible classification for the rater entity of a construct is the *group*. The group, in marketing, is usually a sample of consumers or industrial buyers, but sometimes a sample of managers, salespersons, or general employees. These are other than a group of experts (above).

The object for group ratings is usually a COMPANY or a PRODUCT or an AD and the purpose of the construct is to derive an attribute score for the object (in Peterson's, 1997 meta-analysis, about four in 10 of the scales were “stimulus-centered,” that is, they were used to rate an object). The score is projected to or “based on” the population of which the group is a sample. As we will see, the reliability (precision) of scores depends mainly on the group sample size.

Examples in which the rater entity for the construct is the group would be SATISFACTION among CUSTOMERS of McDONALD'S RESTAURANTS; or the QUALITY of IVORY SOAP as perceived by the NON-USERS OF THE BRAND; or the VRP of a new INTEL AD among typical TV VIEWERS.

In summary: The rater entity is an intrinsic component of a marketing construct. The rater entity can be identified as the individual, experts, or a group. The rater entity largely determines how reliability (precision of scale scores) should be assessed and reported. Reliability is discussed in Section 4.

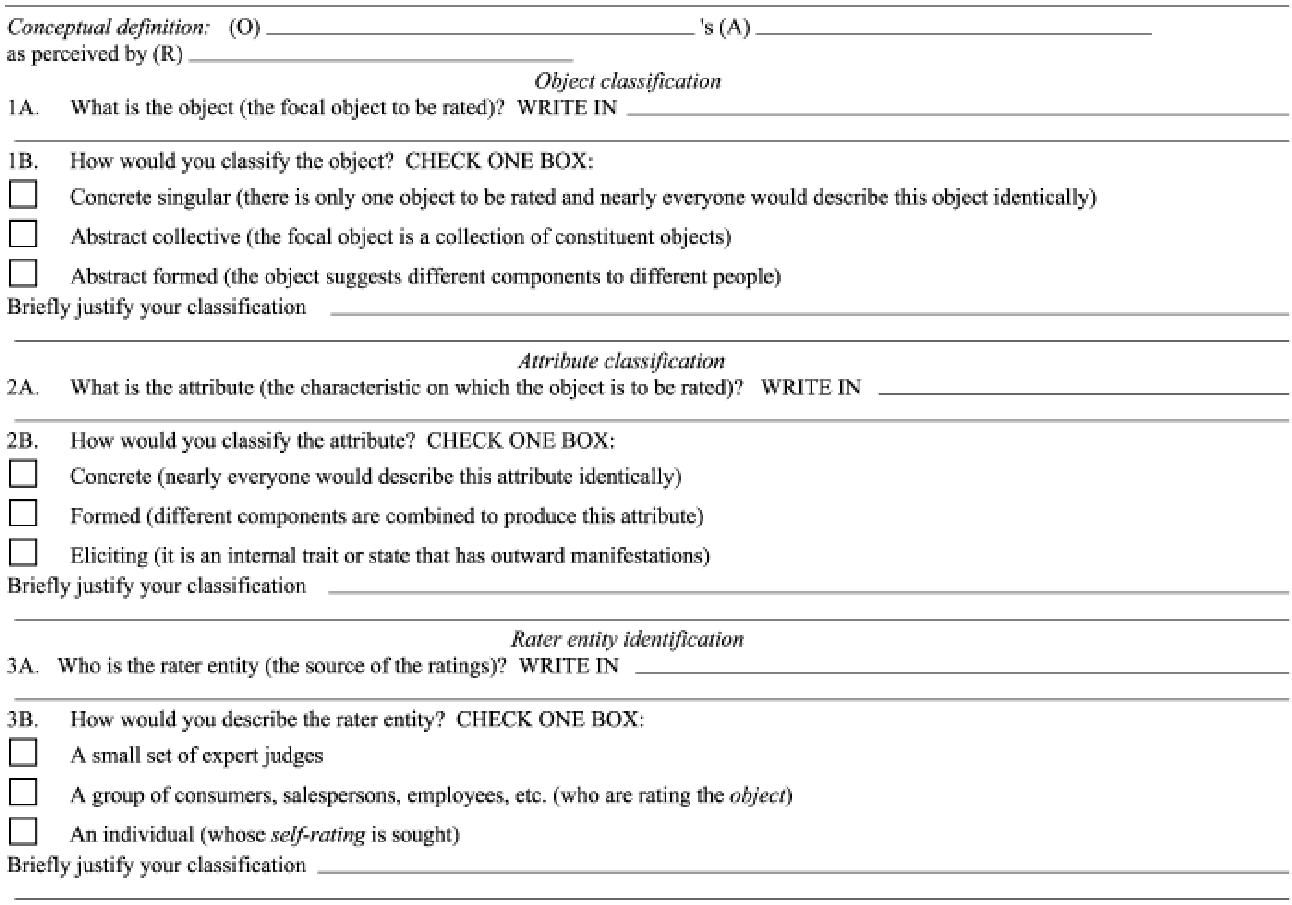
An *overall* summary of object–attribute–rater (O-A-R) types in C-OAR-SE can now be made. The classifications for object, attribute, and rater entity are shown in Fig. 2. A prototype expert judges' rating form is provided in Table 2.



The arrow at the top indicates that the object is “projected onto” the attribute. The two arrows from the rater entity indicated the rater is perceiving both the object and the attribute.

Fig. 2. Object–attribute–rater entity classifications.

Table 2. O-A-R expert judges' rating form



Conceptual definition: (O) ____________________ 's (A) ____________________
as perceived by (R) ____________________

Object classification

1A. What is the object (the focal object to be rated)? WRITE IN ____________________

1B. How would you classify the object? CHECK ONE BOX:

□ Concrete singular (there is only one object to be rated and nearly everyone would describe this object identically)

□ Abstract collective (the focal object is a collection of constituent objects)

□ Abstract formed (the object suggests different components to different people)

Briefly justify your classification ____________________

Attribute classification

2A. What is the attribute (the characteristic on which the object is to be rated)? WRITE IN ____________________

2B. How would you classify the attribute? CHECK ONE BOX:

□ Concrete (nearly everyone would describe this attribute identically)

□ Formed (different components are combined to produce this attribute)

□ Eliciting (it is an internal trait or state that has outward manifestations)

Briefly justify your classification ____________________

Rater entity identification

3A. Who is the rater entity (the source of the ratings)? WRITE IN ____________________

3B. How would you describe the rater entity? CHECK ONE BOX:

□ A small set of expert judges

□ A group of consumers, salespersons, employees, etc. (who are rating the *object*)

□ An individual (whose *self-rating* is sought)

Briefly justify your classification ____________________

2.5. Scale formation

2.5.1. Object item parts and attribute item parts

Scale formation in C-OAR-SE is a matter of putting together object item parts with their corresponding attribute item parts to form scale items—technically, to form the *stems* of the scale items, as the response alternatives or *leaves* have also to be added for each item (see next section). For example, if IBM is the concrete singular object and it is to be rated on SERVICE QUALITY regarded as a formed attribute consisting of eight components such as Response time, Reasonable hourly rate, Solution satisfaction, and so forth, each represented by one concrete item part, then eight items (1×8) would result. If alternatively IBM were for some reason to be regarded as an abstract collective object with, say, three branch offices of IBM available for a typical customer in a large city to call for service, then 24 items (3×8) would result. To give another example, if CAPITALISM is regarded as an abstract formed object with three components of Free enterprise, Profit seeking, and Material gain and these could each be represented by, say, three concrete items (in the opinion of the expert judges) and the attributes are ECONOMIC DESIRABILITY and SOCIAL DESIRABILITY and are regarded as concrete, then 18 items (3×3×2) would result.

The number of items needed to form the scale is the same regardless of whether the rater entity is an individual, a panel of experts, or a larger group of target population raters. However, the content (wording) of the scale items is certainly not independent of the rater entity. The items must be easily comprehended by the target raters, and pre-testing is needed to ensure this.

2.5.2. Pre-testing scale items

The best method for pre-testing scale items is *cognitive interviewing*, which includes extensive probing and think-aloud answers to the rating questions, and to the answer categories, to ensure they are understood as intended (Schwarz, 1999). An excellent application of cognitive interviewing to improve scales is detailed in the study by Bolton (1993), in which this method resulted in higher validity and reduced data collection costs.

Nevertheless, the important step of pre-testing items for meaning is hardly ever conducted for marketing scales in academic research. Instead, apparently lured by the classic “true score plus random error” model, scale developers tend to write a half-dozen or so “good enough” items in the vain hope that responses to them will “converge on the truth” when the item scores are averaged (a high single-factor loading and alpha are then usually produced to “prove” this has happened). The perceived need for multiple items is often supported by citing Churchill's (1979) viewpoint that “single items are unreliable.” However, Churchill's viewpoint is borrowed from ability-test theory in psychology, where the items differ in *difficulty* and there is within-person variation in *ability* to answer them (see Lumsden, 1978). For ability tests, a single item cannot provide a precise (reliable) estimate of the individual's ability. This is not the case for marketing constructs. Consumers do not require “ability,” other than basic literacy, to answer marketing scale items. The items do not and should not differ in “difficulty.” For completely concrete constructs, one concrete item is all that is necessary. For abstract constructs, one concrete item for each constituent or first-order component is all that is necessary. The multiple items are used to *cover* the constituents or components parsimoniously. Multiple items should never be used to cover *up* lack of pre-testing for concreteness. Practitioners are far less subject to this criticism (Bolton, 1993, for instance, conducted her study as a practitioner for GTE Laboratories). Cost considerations force parsimony on practitioners and they are more likely to pre-test questions and rating scales to find an unambiguous, efficient solution.

There is an additional type of pre-testing required when the scale includes items measuring a newly conceptualized eliciting attribute. The candidate set of items for the eliciting-attribute scale should first be rated by the expert judges for prototypicality with respect to the attribute. Burisch (1997) describes the purpose of this procedure as to produce "content saturation" of the scale. Webb, Green, and Brashear (2000) provide a good application of the content saturation procedure for developing two new attitude scales.

As mentioned previously in the conceptual discussion of eliciting attributes, an eliciting attribute may be first-order unidimensional or it may be second-order unidimensional with correlated, unidimensional components. For a *first-order* eliciting-attribute scale, where the remaining items from content saturation screening are likely to be 10 or fewer, it is convenient to go straight to the computation of *coefficient beta* (Revelle, 1979; see also John & Roedder, 1981), which is a conservative test of whether there is one general factor (one dimension) in the items.[13]

A minimum β of 0.5 is needed to infer that there is a general factor accounting for at least 50% of the item variance. To improve on this minimum, coefficient *alpha* can usefully be applied to delete items with low item-total correlations (e.g., SPSS, 1988). The desirable targets for an eliciting-attribute scale are a β of 0.7 (70% general factor) and an α of 0.8.

For a second-order eliciting attribute, beta should be computed for the items intended to measure each component and the same values for β and α as above sought for each component. To check the structure of the components in relation to the second-order attribute, confirmatory factor analysis can be usefully applied to all the items—principal components with *oblique* rotation, not Varimax rotation as suggested by John and Roedder (1981) as this would imply uncorrelated components. This will require a fairly large pre-test sample of raters: a minimum of 20 raters for each factor, that is, component, to be extracted (Arrindell & van der

Ende, 1985). The factor structure should represent the conceptualized components. Component scores (not item scores) can then be further beta-checked and *β* should be at least 0.5 for the total attribute scale, indicating the second-order general factor underlying the components. Note that the *β* value here is lower than the 0.7 minimum recommended for components because of the oblique structure. The *α* value for the total score will undoubtedly be high and should be at least 0.7. The problem with omitting beta (or prior confirmatory factor analysis) is that alpha can be high even if the components are zero-correlated, that is, when there is no general factor (see also Cortina, 1993).

Beta (the minimum of all possible split halves) is a lower-bound estimate of internal consistency and alpha (the average of all possible split halves) an upper bound *assuming* that there is a general factor, so alpha is only properly interpretable contingent on a sufficiently high value of beta. Alpha then provides a best summary estimate of precision. The recommended values are *β*=0.7 and *α*=0.8 for components and *β*=0.5 and *α*=0.7 for a second-order eliciting attribute with components.

2.5.3. Response (answer) formats

Likert response formats should not be used—they cannot provide unambiguous, precise item scores (Rossiter & Percy, 1987, p. 547). In the usual item for which Likert responses are used, the intensity is built into the item stem, that is, into the question itself. Example: "I never attend social events." However, in the Likert *answer* format, "strongly disagree" could mean the rater always attends social events, attends many social events, or is simply emphatic that it is not true that he or she never attends them.[14] Even a change of the stem wording to "I seldom attend social events" does not help, because the response is still ambiguous. A further problem due to putting intensity into the stem of Likert items (cf. "never attend" or "seldom attend" in the two versions of the question above) is that the psychological zero or neutral point is lost because "neither agree nor disagree" cannot signify the same neutrality in both versions and in fact does not do so in either. This poses a major problem for the interpretation of Likert-format scale scores. The problem worsens when Likert ratings are summed or averaged over items whose stems vary in intensity (Foddy, 1993, pp. 168–170) because the intensity of the *total* score is obscured irretrievably.

A better practice is to build intensity of response into the leaves of the item, the response alternatives. Items in a multiple-item scale should be worded with intensity-free stems and minimum intensity to maximum intensity answer categories. It does not seem to matter much whether the categories between the minimum and maximum anchoring descriptions are labeled with words, that is, adverbs of intensity, or with sequential numbers (although, for an interesting series of empirical studies suggesting that verbal labels more validly represent people's discriminable states of mind, see Windschitl & Wells, 1996). Basically, there are three response dimensions that characterize attributes: probability (unipolar), frequency (unipolar), or degree (which can be unipolar or bipolar). In all cases, one should clearly identify the psychological zero category, allow separately for a "don't know" category where this is a legitimate answer, and make the adjoining categories has close to equal interval as possible. This is not just an argument in favor of allowing the use of parametric statistical tests but more than this: with a valid psychological zero, a valid minimum and maximum, and equal-interval categories, we have a good approximation of a ratio or "magnitude" scale. Responses in marketing are interpreted as magnitude estimates all the time; for instance, if COKE is rated 10 out of 10 and PEPSI is rated 5 out of 10, consumers, and managers, are likely to interpret that result as meaning that COKE is twice as good as PEPSI, and they would be justified in acting on this interpretation. Also see Nunnally, 1978, Chapters 1 and 2, for the argument that we should grant at least interval properties to carefully constructed scales. He is overly cautious about the existence of psychological zero points needed for ratio scales but the scaling studies referenced below show clearly that these points are interpreted as zero by raters.

For *numerical* scales, which can be used for probability, frequency, or degree, five to seven categories seems to best fit the number of psychological discriminations that most consumers can make with regard to an attribute.[15] For unipolar ratings, there is also a common-sense case for the numerical scale of 0 to 10, an 11-point decile scale, because we have been so well trained to discriminate in decimal degrees. (Later, in the Enumeration step of C-OAR-SE, it is recommended that all scale results be transformed to a 0 to 10 scale for reporting purposes, and this linear transformation does require an interval scale of the original.)

For *verbal* response categories, equal-interval adverbs should be employed or, for probability, equal-interval adjectival phrases. The verbal response categories, of course, have to be converted to numbers for data analysis.

For probability ratings, the descriptors “impossible” (0), “unlikely” (0.15), “slight chance” (0.30), “toss up” (0.50), “likely” or “good chance” (0.70), “pretty sure” (0.80), and “certain” (1.00) provide interval-scalable equivalents for US students, as found by Wallsten, Budescu, and Zwick (1993). This is a valuable finding given many people's discomfort with expressing numerical probabilities (yet they seem to have little difficulty with the probability-equivalent decile scale). For relative frequency ratings, the adverbs “never” (0), “sometimes” (1), “usually” (2) and “always” (3) provide equal intervals by magnitude estimation, again for US students (Bass, Cascio, & O'Connor, 1974). Absolute frequencies (e.g., “seen the ad *n* times”) or rates (e.g., “once a year,” “twice a year,” etc.) could alternatively be used provided that reasonably accurate recall by respondents can be assumed. For ratings of degree, the adverbs “not at all” (0), “slightly” (1), “quite” (2), and “extremely” (3) provide equal intervals by the method of successive-intervals scaling (see Cohen's, 1987 summary of the ratings obtained by Cliff, 1959, again with US college students). It is noteworthy that these are the three recommended adverbs for the scale categories on either side of “neither” in the classic semantic differential technique and are scored −3 to +3 (Osgood, Suci, & Tannenbaum, 1957).[16] An appropriate verbally labeled, bipolar, single-item attitude scale, again with the numbers shown only to indicate scale values, would be: “My overall evaluation of this brand is: (−3) extremely negative, (−2) quite negative, (−1) slightly negative, (0) decidedly neutral, (+1) slightly positive, (+2) quite positive, (+3) extremely positive, □ don't know.” Attribute scales should carry a box next to them for raters to indicate “don't know” when this is a legitimate response alternative to the “decidedly neutral” response that 0 implies. With bipolar attributes, in particular, failure to allow for these two different responses is a large source of score error Grichting, 1994 and Voss et al., 2000. “Don't know” respondents should be analyzed separately as this response signifies unawareness, as compared with an aware but neutral attitude.

2.5.4. Randomized order

Finally, with multiple-item scales, the order of the items should be randomized to minimize response-set artifacts in the obtained scores. This means randomized presentation across multiple items for objects (constituents or components) as well as for attributes (items within components should be separated). This is quite a strict requirement but necessary if the response correlation or “methods variance” artifact, which is especially likely if the same answer format is used for multiple items, is to be held to a minimum (Andrews, 1984). If both the object and the attribute have multiple-item parts, randomization of the complete set of items should be used, and the items are best presented in separate batteries of no more than five items each (Andrews, 1984).

2.6. Enumeration

2.6.1. Indexes, averages, and single-item scores

Because of the different object and attribute types that it is possible to combine in a construct, the enumeration rules (procedures for deriving a total score from the scale items) will vary. These are summarized in Table 3. It can be seen that they range from a single-item score equaling the total score, to two types of index, a double index, an average, and averages which are then indexed. In only two of the six cells is coefficient alpha relevant and one of these, a concrete singular object rated on an eliciting attribute, corresponds with the traditional (Churchill, 1979) procedure.

Table 3. Scale enumeration rules for the six object-on-attribute cells

	Object	
Attribute		
	Concrete singular	**Abstract collective or abstract formed**
Concrete	Single item score	Index over O_i
Formed	Index over A_j	Index (doubly) over O_iA_j
Eliciting	Average (mean) over A_j	Average (mean) over A_j, and index over O_j

O=object, and subscript *i*'s are item parts for constituents or components. *A*=attribute, and subscript *j*'s are item parts for components.

An index is usually, but not always, a summation of item scores. An alternative combination rule to the summation rule when using formed attributes is the *profile* rule (Law, Wong, & Mobley, 1998). The profile rule is most often the noncompensatory *conjunctive* rule, which applies a minimum level for each component that must be exceeded. An example of the conjunctive rule is Parnes' (1961) index of the CREATIVITY attribute, which is enumerated as scores above the mid-point of the Originality component scale plus scores above the mid-point of the Usefulness component scale. BUYCLASS (Anderson, Chu, & Weitz, 1987) is a scale that should use a conjunctive index. To qualify as a "new task buy," for instance, a buying situation should be rated *conjunctively* as "new" on the Newness component, "extensive" on the Information requirements component, and as having "one or more suppliers, all of which are new to the account" on the Consideration of alternatives component. Instead, the investigators, using the conventional approach, factor analyzed the items, reduced the three theorized components to two, employed Likert answer scales, and then just added the two components' scores, so it is not at all clear what the total BUYCLASS score means. Also, there are some *complex* profile rules that use upper and lower bounds (e.g., the VALS LIFESTYLE typology; Mitchell, 1983).

There is also an alternative combination rule to the usual averaging rule when using eliciting attributes, which is the *multiplicative* rule (again see Law et al., 1998). Perhaps the best-known multiplicative score in marketing would be for MULTIATTRIBUTE ATTITUDE measures; here, Belief-item scores are multiplied by the corresponding Importance-item scores or Evaluation-item scores for each attribute, and then averaged. Another example of the multiplicative rule comes from the fear-appeal literature, where the MESSAGE ACCEPTANCE attribute is predicted by multiplying PERCEIVED THREAT scores by PERCEIVED EFFICACY scores (e.g., Rogers, 1983 and Witte, 1994).

2.6.2. Reporting scale scores

The enumeration rules imply that indexes will receive absolute total scores and items for eliciting attributes will receive averaged scores. Although this distinction is arbitrary, it is useful as a reminder that the items for indexes are all in the scale by definition (they cannot be added to or deleted), whereas the items (actually the item parts) for eliciting attributes are a sample of interchangeable items, and averaging them “back” to the range of the common rating scale preserves this (that is, the score is a sample mean). For indexes, it is useful to transform the absolute scores to a scale of 0 to 10, where 10 is the maximum score. This circumvents the problem of open-ended total scores with indexes by putting all index scores on a common scale that facilitates interpretation and comparison. Actually, there is a good case for transforming eliciting attribute scores also to 0 to 10 scales, if unipolar, and −5 to +5 scales, if bipolar. This would greatly improve understanding of results by nontechnical readers, whose everyday numerical decisions are usually made on a number base of 10. A more exact solution is to convert all scales to standard scores but the above is pretty close and more straightforward to interpret.

When the conceptual definition calls for it, the components (or constituents for a abstract collective object) should be weighted before computing the index score. In Coleman's (1983) four-component measure of SOCIAL CLASS, for instance, Education, Occupation, Income, and Residential area are rated on different numbers of answer categories and will therefore contribute differently to the total score if they are not weighted. Education and Occupation are each given double weight in the index, in accordance with the construct definition that says these are the more important components. Components in formed measures (abstract formed objects or formed attributes) should not be *empirically* weighted, as is typically done in partial least squares analysis by weighting the components by their correlation with the total score. Firstly, this would be tantamount to using statistics to define the construct, which C-OAR-SE definitely opposes, and, secondly, such weighting rarely makes any difference to the total score in that the weighted score correlates very highly with the unweighted score (Nunnally, 1978, p. 606).

The scale's minimum and maximum attainable scores, the theoretical minimum and maximum, should always be explicitly stated when the scale is used in a study. For example, is a “seven-point” scale, as is often used for answer categories when rating eliciting attributes, a 0 to 6 scale, or a 1 to 7 scale, or a −3 to +3 scale? It matters when interpreting the reported scores. Graphical presentations of scale scores also should indicate the theoretical minimum and maximum; articles abound in which the reader learns, after close inspection, that the obtained mean difference was, say, 5% of the scale length, or that both means were absolutely so low as to be of little practical import. Behavior intention scales are notorious for this; in many studies, the low mean results indicate that hardly anyone in the experimental group would buy the product (or take other action) even if the mean is significantly higher than that of the control group. Also, behavior intention scores *should* be weighted using empirically proven weights (see Rossiter & Percy, 1997, pp. 567–568).

It is also preferable to indicate the polarity of the scale (see specifically Schwarz, 1999). It is quite clear that a mid-point score of 0 on a −3 to +3 bipolar attitude scale is the psychological zero, but the psychological zero on a scale marked 0 (would not buy) to 6 (definitely would buy) is not at the mid-point, 3, but at the minimum, 0, as this is a unipolar attribute. A reliability (precision) estimate should also be reported for each scale's scores in the particular study; see Section 4. This indicates how accurate the results are. The calculation and reporting of effect size also helps to indicate practical importance when scale results are being compared.

Marketing researchers could do a lot more to give enumeration of scales a common-sense meaning, as the above recommendations suggest.

3. Construct validity and predictive validity

The C-OAR-SE procedure for scale development relies totally on content validity to prove that it provides better measures than does the traditional procedure. Traditionalists will ask: what about tests of construct validity (the multitrait–multimethod test particularly) and predictive validity (does the C-OAR-SE-produced measure correlate more highly with a criterion measure)? As will be shown in the next two sections, both these widely used types of validity are not conclusive.

3.1. Construct validity (MTMM)

The multitrait–multimethod matrix (MTMM) cannot be used to decide whether a C-OAR-SE measure is better than a traditional measure. MTMM poses a paradox because it presumes the old measures are themselves valid. To show convergent validity, the new measure would have to show that it is highly correlated with the very measure it claims to be superior to; not only this, but a high correlation would not show *which* of the two measures is valid—it could be the old or it could be the new. As an example of this, Smith (1999) created a modified SERVQUAL scale in which 40% of the items were attributes that a literature search indicated were important in consumers' evaluations of the service object: FAMILY-PLANNING CLINICS. Despite its logically greater content validity, the new scale correlated very highly with the original scale, thus showing "convergent" validity but not showing which was the more valid scale. For the same reason, "divergent" validity, if it pits the C-OAR-SE measure against traditional measures of *other* constructs, would not be conclusive. Indeed, there is no point in conducting MTMM even if all the measures being compared have correctly been produced by C-OAR-SE.[17] Validity should be established for a scale independently, and as far as possible, absolutely, not relatively via its correlation or lack of correlation with other measures.

The failure of MTMM construct validation to prove validity is seen most acutely with scales that measure abstract collective objects, abstract formed objects, or formed attributes, which do not adhere to the classical domain sampling model. For these, the component items are in the scale by definition; they are *not* interchangeable. It is therefore impossible for other measures—other combinations of items—to be equivalent to the C-OAR-SE measure. In C-OAR-SE, one measure *is* always better than others because it is more content valid.

3.2. Predictive validity

Predictive validity, the extent to which a C-OAR-SE measure correlates with some criterion or outcome measure, is also inappropriate *if* predictive validity is interpreted in its usual sense of trying to *maximize* that correlation. For a multiple-item measure, a "pruning" procedure in which items are selected because of their ability to increase the correlation with a criterion, as in the traditional approach, reduces the validity of the measure. This is because the ultimate would be a predictive measure which measures the same construct as the criterion (it would predict it with r=1.0) and which thereby ignores the fact that there is, presumably, a true construct-to-construct correlation (like a population score) that is definitely not 1.0. For example, from meta-analysis, the true correlation between high-involvement ATTITUDE and subsequent BEHAVIOR is estimated to be *r*=0.4 (Kraus, 1995; see also Rossiter & Percy, 1997, p. 271). To then seek other measures of the predictor construct (like taking sample statistics) that try to *improve* on the population correlation would be improper. For example, by adding BEHAVIOR INTENTION items to the ATTITUDE measure, the correlation could be raised above 0.4, but then this "predictively more valid" measure would be drifting away from the original construct of ATTITUDE, defined as an overall evaluation. As argued by O'Grady (1982), the targeted magnitude of explained variance between two constructs should be "limited to the relation between the constructs as postulated by the theory" (p. 775). He points out, moreover, that predictor variable correlations of considerably less than unity are to be expected whenever the criterion has multiple determinants, which is usual in marketing.[18]

Furthermore, predictive validity has been suggested as the "only way" to validate index measures of constructs (read: any measure that is not based on a concrete object and an eliciting attribute, the two classifications presumed in Churchill's procedure and in structural equations modeling [though not partial least squares—see Fornell and Cha, 1994]). Thus, the formidable authority Bagozzi (1994, p. 333) comments that "the best we can do to assess reliability and validity [of index measures] is to examine how well the index relates to measures of other variables (e.g., test–retest reliability [which is not another variable!]; criterion-related validity [predictive validity])." Diamantopoulos and Winklhofer, for example, recommended and followed the predictive validity approach in their 2001 paper on index measures. This "bootstrapping" approach to validity assessment is just not rational. A scale's validity should be established *independently* for the construct, by using the C-OAR-SE expert judgment procedure.

Predictive validity, if desired in addition to content validity, is relevant in only one sense: a new measure, such as produced by C-OAR-SE, can be evaluated as predictively valid *if* one knows the true construct-to-construct *population* correlation and reconceptualizes the test as one of coming closest to achieving *that* correlation. This is hardly ever the situation in marketing, because the correlation is usually sampled with imperfect measures. The same argument—that of approximating population correlations—applies to so-called *nomological* or “theoretical nextwork” validity (Bagozzi, 1994) although here, the population correlation is usually a partial correlation after removing the contributions of other determinant constructs to the criterion construct's score. The measures produced by C-OAR-SE—shown first to have very good content validity by the C-OAR-SE procedure—should enable better estimates of these population correlations or partial correlations, which will contribute to marketing and buyer behavior theory.

4. Reliability

The rater entity makes a fundamental difference to the way reliability is assessed. Reliability is an estimate of the precision of a *score* obtained from a scale (Weiss & Davison, 1981). A score from a scale can be assessed for reliability (precision) but not the scale itself. To be useful, both theoretically and practically, the score has to come from a valid scale. Highly precise, reliable scores can be obtained from nonvalid scales, and high reliability, per se, says nothing about validity. This well-known fact bears repeating because of the quite widespread tendency, mentioned at the outset of this article, for users of the traditional scale development procedure to report a high alpha as implying high validity, in that alpha is the sole justification provided for employing the scale. Content validity of the scale must be convincingly established before precise scores can be taken to mean what they are supposed to mean.

Test–retest reliability can be dismissed immediately. If people give different answers to the same items on two occasions for no good reason, then all this says is that items are ambiguous and not sufficiently concrete, a content validity issue. Testing and retesting is appropriate when the purpose is to measure change in the person or other object taking the test but the two sets of scores *presume* the validity of the test (Lumsden, 1978). Test–retest reliability provides no information about the precision of scores obtained from the test.

The reliability of scores from a particular application of the scale is the correct interpretation of the term “reliability.” There is no general reliability statistic that is an inherent property of the scale. In particular, coefficient alpha, when used appropriately for an eliciting attribute, does affect precision but *never* alone, as the discussion below will make clear. On the other hand, the nature of the rater entity always affects the way precision is estimated.

4.1. Individual rater

With individual self-ratings, the reliability implications depend on the type of attribute. If the attribute is concrete, as in a self-report of AGE or INCOME, there is no question of unreliability. The individual *gives* a precise score, assuming he or she is not lying or incompetent, and multiple items are not needed.

If the attribute is formed, such as an individual SALESPERSON's self-rating on items that measure CUSTOMER ORIENTATION, a different argument applies but it leads to the same conclusion. Presume here that a finite set of activities has been identified that "add up to," that is, form the attribute of, CUSTOMER ORIENTATION. This is not a sample of activities, as implied in the conventional scale development procedure employed by Saxe and Weitz (1982), but a comprehensive list of the main component activities (ratified by expert agreement). For a formed attribute, there is also no question of unreliability. Assuming that the salesperson understands the items and rates himself or herself truthfully, the individual's score will be perfectly precise and thus reliable. It may be commented here that the truthfulness consideration is one of *validity*, namely, whether the self-report question measures what it is supposed to measure.[19] No number of additional items, the standard way to increase reliability, would compensate for lack of validity and produce a "better" score. Again, when the rater entity is the individual, who is performing self-ratings on items making up a formed attribute, the individual's score on the scale has to be regarded as completely precise.

If the attribute is eliciting, as in a PERSONALITY TRAIT or a PERSONAL STATE, the reliability estimate is not so straightforward. The items are a sample of the eliciting attribute's proximal consequences and thereby of the attribute itself. It follows that precision, as in all sample estimates, depends on sample size (number of items). For the purpose of estimating how precisely the items sample the attribute, the eliciting case is the *only* case among constructs where coefficient alpha is helpful.[20] Given content-valid items, given unidimensionality, and given that the items measure activities and not trivial synonyms, alpha can be taken as an estimate of how precisely the underlying trait has been sampled. For example, α=0.7 means that the set of items in the scale are a 70% precise sample of the trait, whereas α=0.9 means 90% precision (for the reliability coefficient of correlation, alpha in this case, the simple correlation *r* is used, not *r*-squared; this the "true score=observed score×scale reliability" correction recommended by Nunnally, 1978, p. 240)[21] An implication of this is that alphas of at least 0.67 should be sought if no more than a third of the contribution to obtained scores is to be due to the influences of other constructs. For measuring an eliciting attribute, three to five good items that yield α between 0.7 and 0.8 is ideal. Short scales with alphas higher than 0.8 (rounded) are suspicious because the items are almost surely overly synonymous.

4.2. Experts

In content analysis, each attribute of the object (e.g., an AD, or perhaps an INDIVIDUAL, as in experts' assessments of an individual's personality) is represented by a single item rated on multiple answer categories. The precision of the item's score depends on the degree of agreement between the experts (the analogy with inter-item consistency in coefficient alpha should be evident when it is realized that the experts are, in effect, "multiple items" that are sampling the content category). The degree of agreement in turn depends firstly on the number of experts (more judges means more items, in effect, and this provides a better estimate of agreement, up to a fairly rapid asymptote), secondly on the concreteness of the rating *categories* specified for the attribute (concreteness being earlier defined as the degree of lack of disagreement across individuals, so that if concrete categories are selected expertly in the first place, inter-judge agreement should be high), and thirdly on the number of categories for the attribute, to correct for chance agreement. Rust and Cooil (1994) provide a very good formula, the Proportional Reduction in Loss formula, for making the precision estimate, and they point out that alpha is a special case of PRL.

Because the scarce availability of experts usually means they are few in number for a particular study, it is imperative to strive for concrete wording of the rating categories and to include as many categories as can meaningfully be distinguished. With C-OAR-SE, for instance, there are three categories for each of the judgments O, A, and R. If an average of 67% agreement across experts can be attained, as seems reasonable, then 88% reliability (precision) would be likely with three experts, 91% with four, rising to 100% with 11 experts (Rust & Cooil, 1994, p. 8, Table 4).

4.3. Group

Because the projection is to the population of people, the reliability (precision) of the score, assuming a random sample of persons, depends almost entirely on the size of the rater group, that is, sample size in the everyday meaning of the term, because the n (actually $\sqrt{n}$) is the divisor in the standard error of the estimate. The larger the sample of raters, the smaller the confidence interval around the observed score and the more precise it is. For instance, in general, with a 95% (of scores) confidence interval, scores from a sample of 25 consumers will be up to ±20% imprecise, whereas those from a sample of 500 consumers will be up to ±4% imprecise, the "up to" referring to the nearness of the observed score to the middle of the possible score range, e.g., 50% on a percentage scale, where standard errors are largest (see Rossiter & Percy, 1997, p. 552, and note that they provide averaged "look-up" tables whereas, strictly speaking, the confidence interval should be estimated from the standard deviation of the data). The 95% CI is arbitrary, of course, though it is becoming widely accepted in the biomedical sciences, where serious health decisions are made. Market research practitioners, notably Information Resources, often use an 80% confidence interval (e.g., Lodish, Abraham, Kalmenson, Livelsberger, Lubetkin, Richardson, Stevens, 1995) which carries a 20% Type I error risk; so when comparing two scores, such as sales results from an experimental sample and a control sample, there is a 20% chance of wrongly detecting a significant difference. This seems like too little confidence or, the same thing, an unjustifiably high level of precision in reporting the scores. On the other hand, 99% seems unrealistically conservative for most scale-score applications in marketing. Hence, the recommended 95% CI. A common-sense way to make the confidence-interval precision estimate comparable to the 0 to 100% type of estimate, as in the PRL, would be to refer to plus-or-minus in terms of 100 minus the maximum error that can occur; thus + or −20% becomes a maximum error of 40%, and thus 60% precise, + or −4% becomes 92% precise, and so forth.[22]

There is one important additional precision factor when groups are rating an object in terms of an eliciting attribute. An example would be CONSCIENTIOUSNESS, one of the big five personality traits, as a national trait of CHINESE PEOPLE as rated by NORTH AMERICANS. The additional factor, from the foregoing discussion, is the precision of the scale for the eliciting attribute itself, which is typically estimated by alpha. Although such a combined precision estimate has not, apparently, been attempted, a good guide might be sample size precision *divided by* α (e.g., a±4% error for a sample size of 500 would become, if α=0.8, ±4%/0.8, or ±5%). Again, the 100% minus maximum error, rounded, interpretation can be reported.

The reliability estimation formulas according to C-OAR-SE are given in Table 4. The appropriate method for estimating scale-score reliability differs according to the rater entity and the type of attribute in the construct. If the rater entity is the self (self-ratings) and the attribute is either concrete or formed, then the reliability of the individual's score is 100% (and in these two cases, reliability does not vary with the application of the scale). If experts are the rater entity, the reliability of the object's mean score increases with the number of experts and number of answer categories in the rating of the attribute. If a group is the rater entity, the reliability of the object's mean score increases with group sample size and decreases with the standard deviation of the ratings, which together provide a confidence interval for the object's mean score on the attribute. Coefficient alpha is incorporated in the reliability estimate only if the attribute is of the eliciting type, as the accuracy of scores is sensitive to the number of items used to sample the eliciting attribute, given that the items have been shown to be unidimensional, though usually over the remarkably small range of three to five items for most eliciting-attribute scales in marketing.

Table 4. Reliability (percentage precision-of-score) estimates for rater entities by type of attribute

	Rater entity		
Attribute	Individual(self-rating) (%)	Panel of experts	Group (of consumers, etc.)
Concrete	100	Average PRL[a] (over object items)	100–95% CI
Formed	100	Average PRL (over object and attribute items)	100–95% CI
Eliciting	100 (α)[b]	Average PRL (over object items, and over average of attribute items multiplied by α)[c]	100–(95% CI/α)[d]

[a] PRL is Proportional Reduction in Loss calculation (Rust & Cooil, 1994).

[b] E.g., if α=0.8, then Precision=100 (0.8)=80%.

[c] E.g., if there are several object items and their average PRL is 85%, and any number of attribute items and their average PRL is 90% and their α=0.8, then Precision=[85+90(0.8)]/2=[85+72]/2=78.5%=78%, rounded down.

[d] E.g., if the 95% confidence interval around an observed score based on a sample of 200 people is ±7% and α=0.8, then Precision=100−(14/.8)=100−17.5=82.5%=82%, rounded down.

5. Conclusions

The message of this article is not going to be popular among academic researchers in marketing, at least not initially. It alleges that much of what we have achieved to date in terms of defining and measuring major constructs in marketing is of suspect validity, which has hindered development of adequate theories and models and produced many fuzzy and untrustworthy findings. Findings based on objectively measured inputs and outputs, such as TV-to-scanner purchase panels, are exempt from this criticism. However, self-report data, which constitute the bulk of our attempts to find out the “why” of marketing behavior as well as to record much of the “what,” remain severely threatened.

C-OAR-SE is offered as a theoretical and procedural solution to the problems of developing scales to measure marketing constructs. C-OAR-SE is primarily a rationalist procedure, asking researchers to think carefully about the nature of constructs (to properly define them), to work much harder up front to generate and select items, often multiple but sometimes just one, for their scales (and not leave it to computers to select items from a pool of items of dubious content), and when designing answer categories and reporting scale results, to give much more consideration to what they really mean (meanings that are too often hidden in statistics that may well be correct procedurally but convey little to other than the authors).

The main lessons from C-OAR-SE can be summarized as follows:

1. A construct, a “phenomenon of theoretical interest” (Edwards & Bagozzi, 2000), must be conceptually defined in terms of the following elements: the object, including its main constituents or components if abstract; the attribute, including its main components if abstract; and the rater entity, the perceiver's perspective being an inherent part of the construct. If any of these definitional elements is missing, scale development to operationally measure the construct cannot properly proceed. Open-ended interviews with a sample of target raters are usually needed to contribute to the concept definition, especially to identify components that may be involved. A panel of several experts must then ratify the object, attribute, and rater entity classifications.
2. The object of the construct can be concrete singular (one-item part needed for it in the scale), or abstract collective (multiple-item parts, one per constituent), or abstract formed (multiple-item parts, one per main component). The scale's object, therefore, and not just the attribute, can be multicomponential. Consumer values are a noteworthy example of multicomponential, abstract formed objects that have been measured completely inadequately with a single item each.
3. The attribute of the construct can be concrete (one-item part). A concrete singular object to be rated in terms of a concrete attribute needs only a single-item scale. Insistence by journals on multiple-item measures for all attributes has led to the practice of adding attempted synonyms that actually decrease the content validity of the measure. On the other hand, many attributes, particularly those in the more complex constructs, are abstract and do require multiple items (multiple-item parts, one per component if formed and several for the attribute, representing its proximal consequences, if eliciting). A majority of attributes

in marketing are formed “composite” attributes, requiring an index of defining items, rather than eliciting “trait or state” attributes, requiring an average of unidimensional indicative items. Failure to correctly classify formed attributes has led to the wrong structure for identifying components and the omission of crucial items. Most of the measures of classic constructs in marketing and also most measures of new constructs in the past five years make this error, and so it continues. C-OAR-SE gives guidelines for correcting these measures.

4. Rating scales' answer categories also need improvement, so as to lessen ambiguity for raters and for users of the research. Likert “agree–disagree” ratings should be abandoned in favor of building degrees of the attribute into the rating categories. Unipolar or bipolar ratings should be chosen appropriate to the psychological zero of the attribute. Bipolar ratings should include a separate “don't know” category. Reporting of scale scores should be improved by giving the theoretical minimum and maximum of the scale in tables and graphs so that effect size is more apparent.

5. From a metatheory-of-measurement standpoint, the recommendations in C-OAR-SE are radical. One is that content validity, which is what C-OAR-SE is based on, is all-important, necessary, and sufficient for use of a scale. A second is that the multitrait, multimethod assessment of construct validity should be discontinued because it cannot be used to decide the validity superiority of alternative measures of a construct. A third is the re-thinking of predictive validity as not being to maximize prediction, but to try to come closest to the true theoretical correlation between the predictor construct and the criterion construct. Finally, reliability, which has become ersatz evidence of validity for many scales, should be regarded as no more than a precision-of-score estimate, reportable not in general, but for each application of the scale.

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Notes

1. The C-OAR-SE acronym is appropriate in that the new procedure is looser and broader than the overly narrow previous procedure. The O-A-R part is set off in the acronym to indicate the three defining elements on a construct: object, attribute, and rater entity.

2. The author is well aware of the later, 1994, edition of Nunnally's classic book but prefers the 1978 edition, where the points relevant to the present discussion are made.

3. One could regard *relationships between* constructs as also being constructs in that they are also phenomena of theoretical interest. However, relationships are usually inferred from prior theory, or from qualitative (phenomenological) research (see Bettman, 1970 and Woodside & Fleck, 1979), or from experiments, and *presume* constructs and therefore their measurement scales. Thus, relationships between constructs is a topic excluded from scale development. Also excluded is *qualitative research* measurement of constructs, in which the nature of objects and especially of attributes is "to-be-discovered" and rater entities are initially consumers and ultimately the qualitative research analyst.

4. We do not mean "multidimensional," a term referring to an *attribute* as having projections of its components "outwards" as "continua" (the dimensions). This term is correct, in C-OAR-SE, only for a *second-order eliciting attribute* (see Section 2.3.3). The term "multicomponential" is preferred in general because it includes the more prevalent situation of components adding "inwards" to form the result, as in an *abstract formed object* or a *formed attribute* (see Section 2.3.2). Note that components can be nominal; they do not have to be continua.

5. An interesting proposal to circumvent the need for multiple component items when rating an abstract formed object, reminiscent of the RVS, was made by Gardner, Cummings, Dunham, and Pierce (1998). These researchers developed a single-item (though elaborate) measure for each of several job-related constructs. An example is for the object JOB FACTORS, where the attribute is FREQUENCY OF THINKING ABOUT THEM AT WORK, and the rater entity is the INDIVIDUAL EMPLOYEE. The "single item" was achieved by priming the respondent with the object's components via a lead-in to the question. Here is the lead-in for rating of JOB FACTORS: "Job factors. These are the things directly related to the work you perform. This includes all of your job duties, the challenge of your job, the activities you engage in, the decisions you make as part of your job, and your job responsibilities" (p. 901). Their prime-the-components approach probably results in a more content-valid rating than use of simply the object, JOB FACTORS. A similar approach was used recently by Novak, Hoffman, and Yung (2000) to measure the FLOW experience, an abstract formed object, among Web users. However, the time required to rate the components would be little more than the time needed to read them and remember them and would be more valid.

6. The description "formative attribute" is not correct because it suggests that it is the attribute that is doing the forming rather than, correctly, that it is the *items* that are doing so. For the opposite reason, the earlier terms "cause indicators" (Blalock, 1964), or "formative indicators" (Fornell & Bookstein, 1982), are not suitable because they refer to the *items* rather than to the resulting *attribute*. Also, describing both types of items as "indicators" is confusing because in the case of formed attributes, and abstract formed objects, the items are *defining*, not merely indicants. In C-OAR-SE, the indicator description of items is applicable only for attributes that are classified as *eliciting*.

7. Law and Wong (1999) give a good example of this distinction for the formed attribute of JOB SATISFACTION. The proximal antecedents of JOB SATISFACTION are satisfactions with specific aspects of the job, such as Satisfaction with Co-workers, Satisfaction with Supervisor, Satisfaction with Pay, and Satisfaction with Facilities. The more remote causes, or distal antecedents, are separate constructs, such as

SUPERVISOR'S LEADERSHIP QUALITY AS PERCEIVED BY THE EMPLOYEE, RELATIVE PAY LEVEL, and probably several others.

8. In no way can the classification of an attribute be determined post hoc by the use of statistical analysis. For instance, discovery of a low alpha for multiple items does *not* mean that the attribute can be ex post facto redefined as “formed” and this interpretation would be a blatant mis-use of C-OAR-SE. Constructs must be defined a priori by expert judgment. Constructs are never produced by statistics except for the contribution of single frequency counts when deciding inclusion of main constituents or components.

9. “Cause” here is meant in the strongest sense of *micromediation*(Lewis, 1977), that is, the “process-linkage” view of causation rather than just the “probability-raising” view. See Cook and Campbell (1979), Zaltman, LeMasters, and Heffring (1982, chapter 3), and Schaffer (2001).

10. Peterson's (1994) meta-analysis of multiple-item scales in marketing also found no gain in alpha beyond five items. He excluded “aggregated” scales from his analysis, that is, he examined only “component” scales (for example, he would exclude SERVQUAL but include its component scales of Reliability, Assurance, etc.), so his finding is relevant to the present issue. The fact that his study would include formed-attribute scales, for which alpha is not relevant but is likely to be lower than for eliciting-attribute scales, means that his number-of-items result is conservative, so that five items is a safe upper limit for measuring a single component of an *eliciting* attribute. He also found that several more items may be needed if the answer categories are dichotomies (e.g., Yes–No), a finding that fits the discussion in Section 4 of the present article regarding score precision.

11. Mowen (2000) developed a 6-item measure of NEED FOR COGNITION (NFC) that compared very well (in his study, α=0.81) with the 18-item version (α=0.84). However, from a content validity standpoint, Mowen's short scale and the original scale have problems. Mowen's scale, obtained with some difficulty by eventually extracting a one-factor solution from correlations of the 18 items and eliminating items with item-total correlations of less than 0.5 (see Mowen, 2000, p. 74), consists of six items that are each negative in the stem (e.g., “I only think as hard as I have to”; “Thinking is not my idea of fun”) and the Likert agree–

disagree answer format is used as the leaf. Whereas agreement with these negative items would indicate *low* need for thinking, it is by no means clear that disagreement would indicate *high* need (see criticism of the Likert answer format in Section 2.5.3). Further, in cognitive interviewing on the items in the long NFC scale, a frequent difficulty was that respondents said, “it depends on the situation,” which defeats the rationale for a stable trait measure (Sherrard, 2001). Finally, the conceptual definition of the NFC construct as “the tendency for the individual to engage in and enjoy thinking” suggests that there are two components involved—Frequency of thinking and Enjoyment of thinking—and that perhaps “need” for cognition should be measured by the multiplicative product of the two responses (see Section 2.6). NFC has been little used in psychology, though it is popular with consumer behavior researchers, and does not appear as a basic trait in the big five or big eight typologies.

12. For state constructs, the direct object is the EXTERNAL STIMULUS that causes the state (this stimulus elicits the eliciting attribute), and the SELF becomes the indirect object (which is incorporated in the self-statement in the attribute item part). For example, for the construct PERSONAL RELEVANCE OF THE AD, the grammatical classifications are of the form: “I (subject and rater entity) rate this AD (AD as object) as PERSONALLY (SELF as indirect object) RELEVANT (adjectival completion of the attribute).” For trait constructs, being general, there is no external stimulus, and the object is the SELF.

13. The formula for coefficient beta is β=min $[(n_i+n_j)^2\bar{\sigma}_{ij}/\sigma_{\mathrm{T}}^2]$, where n_i and n_j are the numbers of items in any and all split-halves of the items, half with items *i* and half with items *j* (they need not be exactly equal halves, as they cannot be for an odd number of total items), $\bar{\sigma}_{ij}$ is the average between-halves item covariance, and σ_{T}^2 is the variance of the total scale score. It would be convenient to have software written to calculate beta as the combinations of split-halves increase rapidly with the total number of items.

14. In an empirical demonstration of this phenomenon, Arndt and Crane (1975) found significant differences in Likert responses to equivalent positively and negatively worded items for 15 of the 20 items in their study. A recent major investigation by Baumgartner and Steenkamp (2001), using items of the typical Likert item type with the attribute intensity in the stem and an agree–disagree response format, found severe

“response style” effects, such as acquiescence tendency and mid-point tendency, which altered scale scores by up to 29% and inflated or deflated correlations between scale scores by more than 50% if the two scales had the same bias. They recommended using balanced item pairs (a positively and a negatively worded item, thus two items instead of one) or else post-correcting for response-style variance statistically. Neither recommendation is practical or likely to be widely followed. The problems may be peculiar to Likert-stem, Likert-leaf items and is a further reason for not using this type of item.

15. See Miller's (1956), famous “magical number seven plus or minus two.” Miller concluded that “there is a span of attention that will encompass about six objects at a glance…and a span of absolute judgment that can distinguish about seven categories” (p. 91). This conclusion has held remarkably well for the types of *single-dimension* discriminations that are required for rating scales (Baddeley, 1994). Perhaps the safest recommendation is five to seven categories for unipolar ratings (or a jump to the 11-point decile scale) and seven categories for bipolar ratings, three each side of the neutral category (which is usual for semantic differential ratings).

16. “Semantic differential” refers to the theoretical factor structure of connotative meaning and not to just any double-anchored answer scale. Heise (1969, p. 414) explains why bipolar adjectival scales are used for semantic differential ratings, rather than unipolar scales or scales with longer descriptive anchors:

“…unipolar ratings may have a markedly different nature from bipolar ratings. When only one adjective is presented, its denotative meaning may have more impact on ratings than when it is used with another adjective, and it may be easier to rate peripheral or fleeting aspects of the stimulus. For example, someone asked if dogs are bad may say ‘some dogs are bad’ and asked separately if dogs are good may say ‘most dogs are good,’ whereas if asked whether dogs are good or bad, he would have to make a single summary statement.”

17. Long before C-OAR-SE, a theoretical critique of MTMM was provided in an important but little-known paper by Lumsden and Ross (1973), who concluded that construct validity is impossible to prove. Their argument was repeated in Lumsden's (1976) more accessible review of test theory in the *Annual Review of*

Psychology; it has not been refuted, yet MTMM testing continues unabated. As Lumsden commented wryly regarding the paradox of logic it is based on: “The multi-trait multi-method procedure seems to require that a test have an identical twin of the opposite sex” (p. 270). He foresaw the solution to the “validity problem” as “via an extension of…content validity” by forcing test constructors to write clear *a priori specifications* for the set of items (pp. 270–271). James Lumsden passed away not long after his landmark review was published. C-OAR-SE, with its insistence on up-front concept definition and classification of object, attribute, and rater entity, continues very much in his spirit.

18. Kenny (1979) goes further in claiming that there is an inherently unpredictable aspect of any behavior and that “one is fooling oneself if more than 50% of the variance [by *r*-squared] is predicted…the remaining unexplained variance is fundamentally unknowable and unexplainable. *Human freedom may rest in the error term*” (p. 9, emphasis in the original). This, of course, is an opinion based on multivariate prediction, referring to *r*'s above 0.7. Univariate predictions (one predictor and one criterion) in the psychological *and* medical sciences almost always are in the range 0.01–0.4, just occasionally reaching 0.5 or higher (Cohen's large effect size) and then mainly in controlled experiments rather than field studies (Meyer, Finn, Eyde, Kay, Moreland, Dies, Eisman, Kubiszyn, Reed, 2001). Univariate predictive relationships in marketing are unlikely to be exceptional in this respect.

19. In the case of CUSTOMER ORIENTATION, there is evidence that SALESPERSONS tend to overrate themselves, averaging about 8 on the 1 to 9 (low to high) scale, compared with INDUSTRIAL CUSTOMERS' ratings of them, which average about 6 on the scale (Michaels & Day, 1985). However, in C-OAR-SE, the rater entity is an inherent part of the construct, and so SALESPERSONS' and CUSTOMERS' ratings would be different constructs.

20. Little known is that Cronbach (1951), shortly after his paper on it, abandoned coefficient alpha in favor of generalizability coefficients. The *idea* of generalizability is represented in C-OAR-SE via item selection for objects and attributes and specification of the rater entity. See Cronbach, Gleser, Nanda, and Rajaratnam, 1972, and for marketing applications of generalizability calculations see Finn and Kayandé, 1997, and

Rentz, 1987. Nevertheless, coefficient alpha remains specifically useful for assessing scales for eliciting attributes, in C-OAR-SE, when preceded by coefficient beta (see Section 2.5.2).

21. See Ozer (1985) for an explanation of why *r* is the appropriate statistic for the coefficient of determination, although for a conservative reply favoring *r*-squared, see Steiger and Ward (1987). Basically, it is a matter of whether one prefers the "common elements" model (*r*) or the "proportion of variance" model (r^2). Effect size estimates (Cohen, 1977, pp. 78–83) use *r*.

22. The argument for the simplified estimates is as follows. Practitioners rarely understand confidence intervals and they tend to regard a statistic as "the best estimate" anyway and treat it as though it were the population figure, that is, the exact true figure. The debates over TV and magazine audience rating figures obtained from somewhat different survey methodologies are serious testimony to this. It seems better, if not entirely correct, to encourage them to say "this rating is 85% accurate—it could be off by 15%" than to ignore precision altogether. For the same reason, correlation coefficients, which mystify many academics, not just practitioners, should be translated into the Common Language Indicator of effect size (Dunlap, 1994). The CLI for a Pearson bivariate *r* of 0.5, for instance, is 67%, meaning that if the score on *X* is above average, there is 67% chance, or odds of 67:33, that the score on *Y* will also be above average. For those interested, the CLIs for *r*'s of .1, 0.3, and 0.7 are 53%, 60%, and 75%, respectively (Dunlap, 1994, p. 510, Table 1).