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Towards unveiling individual differences in different stages of information processing: a clustering-based approach

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Abstract Information Integration Theory (IIT) is a theory of judgment in daily life. Its principal aim is to study the cognitive rules that people use to integrate information when they make a judgment. Traditionally, the identification of individual differences in these qualitatively different integration rules requires individual designs. It also requires the grouping of individuals according to their integration rule, which can be a challenging task, particularly when the data are noisy or when the pattern involves many factors. This paper builds on the cluster analysis tradition for developing a series of clustering procedures that can be implemented for studying, not only individual differences in integration rules, but also individual differences in other stages of information processing. These procedures are intended to simplify the identification of differences in (a) the subjective valuation of information, (b) the integration of the subjective values, and (c) general attitudes before judging.

Keywords Judgment · Information Integration Theory · Functional measurement · Individual differences · Cluster analysis · K-means

Information Integration Theory (IIT) is a theory about the way living organisms (humans in particular) integrate the information that is present in their environment with the purpose to adapt to its changing character. More specifically, IIT is a theory of judgment in daily life (Anderson 1996, 2008). Its primary aim is to reveal the cognitive rules that people use to integrate information when making a judgment; that is, for example, how a person judges the pleasantness of a piece of music as a function of theme, timbre, pitch and rhyme (Makris and Mullet 2003), or how a nurse judges that a patient is probably suffering as a function of

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this patient's apparent difficulty in making social contact and her avoidance of movements (Igier et al. 2007).

IIT posits, based on extensive empirical data, that people place subjective values on different pieces of information and that they combine these subjective values by means of a cognitive algebra dominated by addition, multiplication, and averaging. It studies how they do this indirectly and functionally, that is, it infers from people's judgments of the combined value of two or more stimuli (or pieces of information) the cognitive rules used to arrive at these judgments.

As the situations in which human judgment is operative are extremely diverse, IIT has been applied in most fields of human psychology: cognitive psychology (Birnbaum 2008), developmental psychology (Schlottman 2001), social psychology (Shanteau and Nagy 1979), health psychology (Gamelin et al. 2006), organizational psychology (Louviere and Islam 2008), and methodology (Hofmans et al. 2007), to quote a few. Also, as the techniques used in IIT are based on concrete cases, and do not require any verbalization from the part of the participants, IIT has been successfully applied with a great variety of populations, and in circumstances that can be considered as extreme ones. For instance, this technique has been successfully applied with children with autism (Rogé and Mullet, in press), with children and adolescents blind from birth (Mullet and Miroux 1996), with children aged 3 years (Cuneo 1982), with an alphabet adults (Ouédraoga and Mullet 2001), with adults in post conflict situations (Azar et al. 1999), and with terminally-ill elderly people (Frileux et al. 2004). Moreover, IIT has also been applied in animal psychology (Farley and Fantino 1978). Most of these contributions have been synthesized in several books (Anderson 1991, 1996, 2008).

In most cases, IIT has been applied without paying attention to individual differences; that is, the judgment rule was revealed at the group level, and was assumed to be valid for the whole sample, and, by inference, for the whole population (the nomothetic approach, e.g., Shanteau and Nagy 1979). In a few cases, however, individual differences have been assessed or have been the object of study (the idiographic approach, e.g., Wilkening and Anderson 1982). In principle, the identification of qualitatively different information integration rules in a given sample requires individual designs, in which each stimulus is presented repeatedly, thereby allowing statistical analyses at the individual level in addition to visual examination of the individual data patterns. Based on these individual analyses, individuals can be grouped according to their integration rule (Wilkening and Anderson 1982).

Grouping individual patterns of data can be a challenging task, in particular when the data are noisy or when the pattern is a complex one, that is, involving more than two factors. In addition, the rules of thumb used for grouping patterns, on the basis of visual similarity or on the basis of significance of main effects and interactions, are likely to change from one research team to another. In other words, the assignment of a particular data pattern to one or another integration rule is often more an art than a science.

Because of these reasons, several authors have explored the possibility of identifying individual differences in information integration in a systematic (quantitative) way (e.g., Bonds-Raacke 2006; Finkelstein and Brannick 1997; Mullet and Girard 2000; Teisseyre et al. 2005). These authors "employed a unique combination of the traditional methodological approach of IIT with a new way of looking at the data, namely using cluster analysis" (Bonds-Raacke 2006, p. 544). Characteristic for these studies is that they used cluster analysis at a general level, that is, they applied it to the raw data. In the present paper, we extend this approach by suggesting procedures to examine individual differences in other stages of information processing as well; that is, during the valuation phase, during the integration phase, and during the response phase.

1 IIT as a model of information processing in judgment

The main idea of IIT is illustrated in Fig. 1 (Anderson 1981). According to IIT, a chain of three functions converts a set of stimuli (i.e., S_1, S_2 and S_3) into a single judgment or response (R) as follows: (1) The Valuation Function converts observable stimuli S_1, S_2, and S_3 into concurrent psychological representations (s_1, s_2, and s_3). In other words, this function assigns a value to each stimulus. (2) Through Psychological Integration s_1, s_2, and s_3 are weighted and combined into an overall implicit response r. (3) Finally, the judgment or observable response R is generated by means of the Response Function. In IIT, there are no a prori assumptions concerning the Valuation or the Integration Function; that is, IIT is not a normative theory.

An important point in IIT methodology is that response linearity is promoted by having the participants go through a series of practice trials in which they get accustomed to the response scale and its end anchors (stimuli a little more extreme than the experimental stimuli). Several studies have shown that, when using these procedures, response linearity holds (Hofmans and Theuns 2008, 2010; Hofmans et al. 2007).

In IIT research, it has repeatedly been found that the Integration Function can be described by simple algebraic rules such as addition, averaging and multiplication (for an overview, see Anderson 1981, 1982, 1996, 2008). As the combination of these integration rules along with a linear Response Function gives rise to qualitatively different data patterns, it is possible to empirically differentiate between them. For example, a pattern of parallelism is the typical signature of an additive-type information integration rule, whereas a fan-shaped pattern is indicative of the use of a multiplicative-type information integration rule.

The response of person k to a stimulus compounded of S_{Ai} and S_{Bj} can be written as a function of the psychological representations (s_{Aik} and s_{Bjk}) (see formulae 1, 2, and 3 for an adding, multiplying and averaging integration rule respectively). In these formulae, C_{0k} and C_{1k} represents the intercept and the slope of the response function, whereas the error term e_{ijk} is a random variable that has an expected value of zero (Anderson 1982). Finally, ω_{Ak} and ω_{Bk} account for the fact that s_{Aik} and s_{Bjk} can be weighted differently.

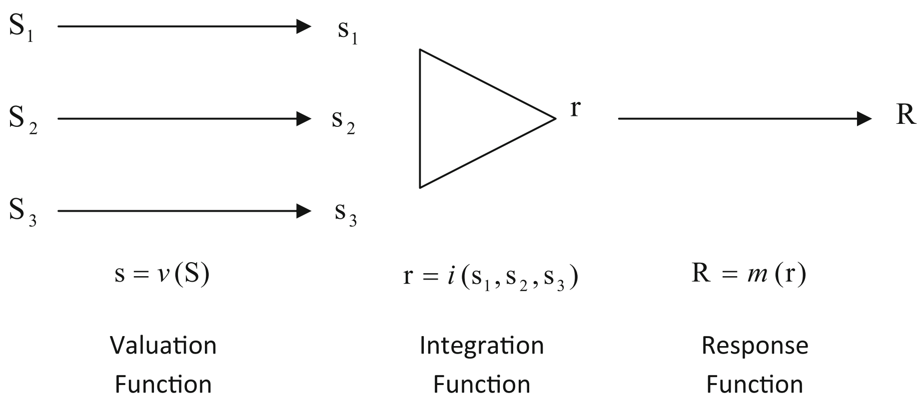

Fig. 1 Information integration diagram with S_n, observable (physical) stimuli; s_n, the subjective stimuli; r, the subjective response; and R, the observable response; v, valuation function; i, integration function; m, response function

$$R_{ijk} = C_{0k} + C_{1k}\left(\omega_{Ak}s_{Aik} + \omega_{Bk}s_{Bjk}\right) + e_{ijk} \tag{1}$$

$$R_{ijk} = C_{0k} + C_{1k}\left(\omega_{Ak}s_{Aik} \times \omega_{Bk}s_{Bjk}\right) + e_{ijk} \tag{2}$$

$$R_{ijk} = C_{0k} + C_{1k}\left(\frac{\omega_{Ak}s_{Aik} + \omega_{Bk}s_{Bjk}}{\omega_{Ak} + \omega_{Bk}}\right) + e_{ijk} \tag{3}$$

Three sources of individual differences appear in the integration diagram of Fig. 1, that is, in the Valuation Function, Integration Function, and Response Function. Because these different types of individual differences may be of substantive importance, each of them should be taken into account, and as a consequence, procedures for capturing these different types of individual differences are required. As indicated earlier, this paper responds to this need by presenting a number of procedures to reveal individual differences in each stage of information integration.

2 Introduction to cluster analysis

Cluster analysis is the name of a group of statistical techniques whose purpose is to group or cluster observations based on the characteristics they possess. It does so by grouping observations that are similar to each other in the same cluster.

In cluster analysis, the solution depends on decisions made by the researcher (Hair et al. 2008). These decisions pertain to the type of clustering, and the choice of similarity and distance measures. In the context of IIT, Bonds-Raacke (2006) suggests that an agglomerative hierarchical clustering procedure together with the centroid agglomerative algorithm is appropriate. The reason is that (1) it uses all data points (unlike single and complete linkage), and (2) it is less affected by outliers than other hierarchical methods (see also Hair et al. 2008).

Throughout this paper, however, we use K-means clustering (Sebestyen 1962), which is a nonhierarchical centroid-based method. The reason is that it also uses all data points, and moreover is less susceptible to outliers and the distance measure used (Hair et al. 2008). A final advantage is that K-means is a well-known method that is implemented in a lot of statistical software packages.

3 Describing individual differences in IIT

3.1 Describing individual differences in how people value information

3.1.1 Theory

One is often interested in how people psychologically judge different types of information. For example, marketers are often eager to know how product name, product packaging, and product price are valued by their customers (Dougherty and Shanteau 1999), or medical professionals may be interested in knowing how their patients judge the disutility of different health states (Gamelin et al. 2006). In the context of IIT, these internal, psychological judgments elicited by the objective stimuli are represented by scale values (s_1, s_2, and s_3 in Fig. 1). It can be shown that IIT is able to provide scale values that are linearly related to the value of the subjective scale values. For example, assuming that an additive Integration Rule holds:

$$\bar{R}_{.jk} = \frac{1}{I}\sum_{i=1}^{I}\left(C_{0k} + C_{1k}\left(s_{Aik} + s_{Bjk}\right) + e_{ijk}\right) \quad (4)$$

$$\bar{R}_{.jk} = \frac{C_{0k} + C_{1k}s_{Bjk}}{I} + \frac{1}{I}\sum_{i=1}^{I} C_{1k}s_{Aik} \quad (5)$$

$$\bar{R}_{.jk} = \frac{C_{0k} + C_{1k}s_{Bjk}}{I} + \bar{s}_{A.k} \quad (6)$$

Because C_{0k}, C_{1k} and $\bar{s}_{A.k}$ do not depend on j, the marginal means of factor B are a linear function of the scale values of factor B, independent of the scale values of factor A (see Veit 1978). For other Integration Rules, similar derivations can be made (see Anderson 1982).

In order to examine individual differences in scale values, (1) scale values are computed from individual IIT analyses, and (2) these scale values are subjected to a cluster analysis. As the Integration Rule is canceled out by Step 1, clustering scale values boils down to clustering a compound of: (1) the psychological representations or scale values, and (2) the Response Function. Because the scale values are co-determined by the null point and unit of the scale (i.e., C_{0k} and C_{1k}), one could consider standardizing the scale values per participant if there are reasons to believe that C_{0k} and C_{1k} are subject to individual differences. Clustering scale values has never been applied in IIT, and is a novel promising procedure, as we will show below.

3.1.2 Illustrative application

In their resuscitation study, Gamelin et al. (2006) used IIT to find valid and reliable measures of patient's utilities for a number of cardiopulmonary resuscitation (CPR) outcomes by manipulating CPR outcome and the likelihood for suffering from this outcome. Individual differences in CPR outcomes may then be captured by clustering scale values for the outcomes, which can be done with two clusters in our example.

Figure 2 shows a pattern of subtle individual differences. In particular, people in Cluster 1 seem to value immediate death in spite of CPR the same as mild irreversible brain damage, and death after a period of intensive care the same as severe irreversible brain damage. The other levels are well separated. For people belonging to Cluster 2, all five levels are clearly discriminated.

In summary, individual differences in scale values can be examined by first computing the scale values in the traditional IIT fashion, then eventually standardizing them, and subsequently clustering them. Because scale values from different factors are independent from each other, they should be standardized separately (per experimental factor), and be subjected to separate cluster analyses.

3.2 Describing individual differences in the integration of information

3.2.1 Theory

The study of the Integration Function has received a lot of attention in studies on information integration. Examples can amongst others be found in intuitive physics, where the principal aim is to study the intuitive understanding of the physical environment that is governed by Newtonian laws (Wilkening and Anderson 1982), or in quality of life research, where

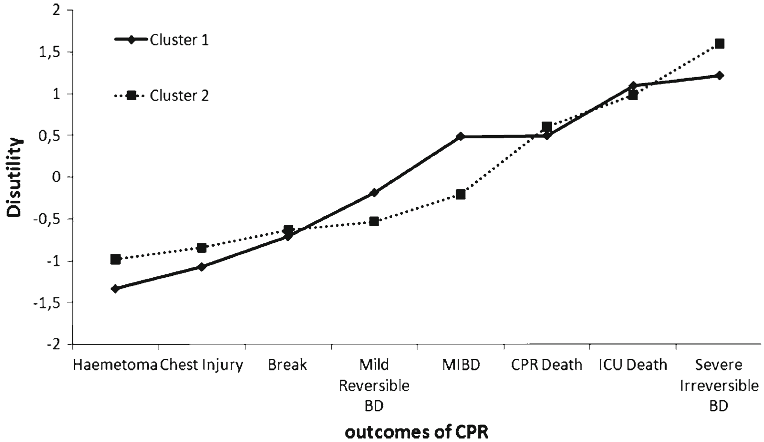

Fig. 2 Disutility (standardized values) for the different CPR outcomes with different curves for both clusters

researchers want to understand how satisfaction with different life domains brings forth a global judgment of well-being (Theuns et al. 2007, 2010).

We propose a two-step approach: (1) in a first step, participants are clustered on the basis of their scale values (see identifying individual differences in scale values), and (2) in the second step, for each cluster of scale values, individuals are clustered on the basis of their standardized responses. The reasoning behind the two-step procedure is the following: (a) individual differences in the valuation function are cancelled by first clustering on the basis of the scale values, and (b) individual differences in the response function are cancelled by clustering on the basis of standardized responses (standardized per participant). As a result, the final clustering reveals individual differences in the integration function only. The procedure for clustering integration rules is novel and has to our knowledge never been applied before.

Note, however, that, while identifying individual differences in scale values requires that there is a separate clustering (and standardization) per experimental factor, this is not the case for this procedure. In this procedure, the scale values of the different experimental factors are subjected to a single clustering (thus constructing a person × scale value dataset with the scale values of all factors in the columns). The reason is that we search for clusters of individuals who have similar scale values for all factors.

3.2.2 Illustrative application

In an intuitive mathematics study, Muñoz Sastre and Mullet (1998) tested how students combine information about bases and exponents when estimating the magnitude of expressions of the type a^n. To detect qualitatively different combination rules, we followed the procedure described above. The result can be seen in Fig. 3.

The results show that qualitatively different combination rules exist. First of all, respondents belonging to Scale Value Cluster 1 integrate base and exponent according to a multiplicative rule, which can be seen from the linear fan pattern. Second, the parallelism for people from Scale Value Clusters 2 and 3 suggests that they use an additive rule. Third, people belonging to Scale Value Cluster 4 use only the base information. Finally, the

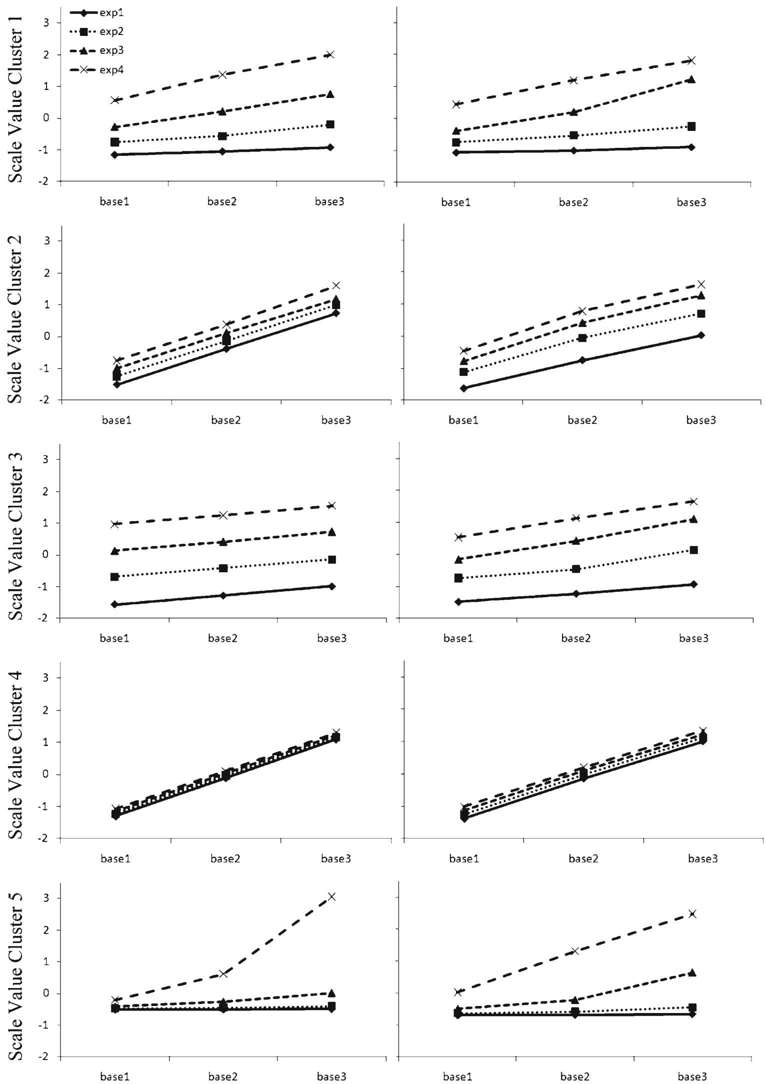

Fig. 3 Estimated magnitude (standardized values) as a function of base and exponent. (1) in a first step, participants are clustered on the basis of their scale values (with different plots for each cluster in the *rows*), and (2) in the second step, for each cluster of scale values separately, individuals are clustered on the basis of their standardized responses (with a different plot for each cluster in the *columns*)

integration rule of respondents from Scale Value Cluster 5 adheres approximately to the normative one.

In summary, qualitatively different integration rules can be revealed by first computing the scale values in the traditional IIT fashion, then searching for clusters with similar scale values across all experimental factors, and subsequently clustering the standardized data for each cluster of scale values separately. Of course, the same integration rules may appear in different scale value clusters (for example, Scale Value Clusters 2 and 3 contain individuals using an additive integration rule).

3.3 Describing individual differences in general attitudes

3.3.1 Theory

Although general attitudes are typically studied using questionnaires, they can be studied in the context of IIT as well. This may be interesting if one has good reasons to suppose that different basic attitudes are associated with the problem at hand, that is, if one has reasons to suspect that there are discontinuities in responses and attitudes. To reveal these individual differences, one may cluster individual means (i.e., averaging the responses across conditions per participant). As the Valuation Function, Integration Function, and Response Function are not of interest when studying general attitudes, they can be cancelled out by averaging. Also this procedure has never been applied before in IIT research.

3.3.2 Illustrative application

In a medical ethics study, Guedj et al. (2006) studied under what conditions lay people and health professionals find it acceptable to break confidentiality when the patient's wife is at risk of contracting a sexual transmitted disease (STD) from her husband.

To study whether individuals differ in their general attitudes towards breaking confidentiality, we computed a single mean per participant by averaging the responses over all experimental conditions. These means were subjected to a K-means cluster analysis and a solution with four clusters was retained. The mean acceptability ratings for these four clusters were 2.96, 8.13, 12.71, and 17.86 respectively. The results correspond to the findings of Guedj et al. (2006), who found two groups close to the extremes (labeled "always acceptable" and "never acceptable") and two of them closer to the midpoint of the scale. This illustrates that clustering individual means allows one to identify individual differences in general attitudes.

4 Discussion and limitations

In behavioral sciences in general, and in the field of judgment and decision making in particular, one of the main sources of data variability is the presence of individual differences. Often these individual differences have substantive interest (see Brusco et al. 2008), while in practice they are often ignored (Anderson 2001, p. 19). One of the reasons may be the lack of techniques to identify these differences. In this paper, we have presented a number of easy-to-use clustering procedures that allow one to describe individual differences of a qualitative or of a quantitative character in the valuation of stimuli, the integration of stimuli, and general attitudes towards these stimuli.

Although we framed the clustering procedures within IIT, they generalize beyond this particular framework. The reason why, in this paper, IIT has been chosen for presenting these procedures is that linearity of the Response Function is crucial for unraveling the different components of information processing. Indeed, when the Response Function is nonlinear, the patterns that are predicted by the different integration rules change and the scale values no longer equal the marginal means, which means that is becomes impossible to infer about the Valuation, Integration, and Response Function (Anderson 1982, 2001). However, as (Anderson 2001) notes "if response linearity can be established in one situation, similar procedures may be expected to yield linear responses in other situations" (p. 699). This suggests that the procedures that are described in the present paper can be used within other frameworks that use similar designs as well.

For carrying out these procedures, we chose K-means clustering because, as indicated earlier, it uses all data points, is less susceptible to outliers than other methods, and is a well-known method that is implemented in a lot of statistical software packages. Another method may yield a different solution as the clustering often depends on the specific clustering method. Note, however, that the procedures proposed in the present paper are by no means linked to a specific clustering method. In fact, they only involve the data pre-treatment needed to reveal the different types of qualitative or quantitative individual differences.

An inherent problem with cluster analysis is the selection of the number of clusters (Steinley 2006). Different methods, along with the interpretability of the solution may help in deciding about K (for an overview, see Steinley 2006). In particular, one may evaluate at which K important qualitative changes no longer occur, that is, at which K further differentiation of the individual differences structure adds little from a substantive point of view.

A final issue is the stability of the clustering. One option to test this is to run the experiment multiple times on the same subjects and then evaluate whether the clustering is the same on these different measurement occasions. Another possibility is to make use of re-sampling methods such as bootstrapping. A final alternative is to cross-validate the cluster results with covariate data. For example, Mas et al. (2009) studied (a) the way physicians treat terminally ill patients, and (b) the frequency with which they visit them. Analyzing the treatment data, they have found four qualitatively different clusters of physicians, which were shown to also hold for the visit data. That the same four-cluster solution hold on two different sets of data strengthened their conclusion that four different medical philosophies exist regarding treating and visiting suffering patients. At the same time, it validated the clustering technique they used.

In sum, the wide variety of applications throughout the paper illustrates that accounting for individual differences in information processing can be interesting from a substantive point of view. This paper provides a set of novel procedures that applied researchers can use for studying them in one or more stages of information processing. Moreover, we are of the opinion that clustering as a tool for identifying individual differences is useful even if there are no natural subgroups. In that case our procedures subdivide the individual differences space into meaningful subgroups on the basis of values, integration rules or general attitudes, thereby highlighting the major patterns that are present in the data.

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