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Running head: SELF-STRUCTURAL MEASURES

Clarifying the Measurement of a Self-Structural Process Variable:

The Case of Self-Complexity

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Abstract

Despite the importance of self-structural variables to understand self processes, research in this area has been hampered by measurement problems. The current study sought to clarify this situation by examining the interrelationships among six self-structural measures of trait-sorting data of 252 Chinese college students: the H statistic of self-complexity, the hierarchical attribute class number, the number of self-aspects, the overlap among self-aspects in terms of traits describing them, the average inter-aspect correlation, and the self-concept compartmentalization Phi . It was found that H was highly correlated with the hierarchical attribute class number, and overlap was highly correlated with the average inter-aspect correlation. Both H and the hierarchical attribute class number were highly correlated with the number of self-aspects; although both the former measures were positively correlated with overlap and the average inter-aspect correlation in general, the relationships were like an inverted U curve. Self-concept compartmentalization was negatively correlated with both overlap and the average inter-aspect correlation. Four main implications of these findings lead to recommendations being made for future studies of self-structural variables, such as self-complexity, self-concept fragmentation and self-concept compartmentalization and their relationship to well-being.

Key words: self-structure, self-complexity, fragmentation, compartmentalization

CLARIFYING THE MEASUREMENT OF A SELF-STRUCTURAL PROCESS
VARIABLE: THE CASE OF SELF-COMPLEXITY

Contemporary self-researchers (e.g., Hattie, 1992; Linville & Carlston, 1994; Markus & Wurf, 1987; Marsh & Shavelson, 1985) regard the self as a multifaceted construct. Within this construct, a distinction has been made between the content and the structure of self-concept (Campbell, Trapnell, et al., 1996; Segal, 1988). The structure of the self refers to “how the knowledge components or specific self-beliefs are organized” (Campbell, Trapnell, et al., 1996, p. 141) and its importance has been highlighted by many self researchers (e.g., Campbell, Assanand, & Di Paula, 2003; Hattie, 1992; Marsh & Hattie, 1996).

To date most of the work from a structural perspective has been factor analytic in nature. Such research seems to have largely run its course perhaps because it implies a relatively static view of self and also seems to assume most people share the same factor structure. As Hattie (2003) argues, much more work is needed on the integrative processes individuals use to form their own conception of self. How these processes may vary across individuals is little known. One reason for the minimal progress in this area is problems with the measurement of the process structural variables themselves.

Over the years, a number of structural variables have been proposed from different perspectives to describe variations in the way self-knowledge is structured across individuals. For example, Linville (1982, 1985) adopted the term self-complexity to represent the differentiation in the self-structure in terms of the number and the distinction of self-aspects; Showers (1992) championed self-concept

compartmentalization, the extent to which positive and negative self-beliefs are separated into different self-categories; Donahue and her associates (Donahue, Robins, Roberts, & John, 1993) focused on another aspect of the self-structure—self-concept differentiation, defined as the degree to which an individual’s self is consistent or fragmented across personal roles; Campbell (1990; Campbell, Trapnell, et al., 1996) proposed self-concept clarity to indicate the extent to which the beliefs in the self-structure are clearly and confidently defined.

According to Campbell, Assanand, and Di Paula (2000, 2003), these variables describe two primary types of structural features: (1) integration—the degree of unity in the self-structure or the consistency across various roles, such as self-concept clarity (Campbell, 1990; Campbell, Trapnell, et al., 1996), and self-concept fragmentation¹ (Donahue et al., 1993); (2) differentiation—the degree of pluralism in the self-structure or the number of different facets that individuals use to think about the self, such as self-complexity (Linville, 1985, 1987) and self-concept compartmentalization (Showers, 1992).

Most of the self-structural variables seek to explain not only how the knowledge components of the self are organized but also how the self-structure is related to psychological functioning. “The fundamental assumption underlying most of these models is that the nature of the interrelations among the self-components is related to psychological well-being” (Donahue et al., 1993, p. 844). Although some empirical support for each of these variables has been reported in terms of their relationships to psychological adaptation, the literature has been characterized by inconsistent results, especially regarding self-complexity. For example, recent meta-analyses found the

relationships between self-complexity and well-being varied from strongly positive to strongly negative (Koch & Shepperd, 2004; Rafaeli-Mor & Steinberg, 2002).

Furthermore, relatively few empirical studies have examined the relationships among the integration/differentiation self-structural variables, and thus how they are linked to each other is still unclear. While all the self-structural variables discussed above are conceptually distinct from each other, inconsistent results have also been reported about their relationships in empirical studies. For example, theoretically, self-complexity describes a different characteristic of the self-structure from that of self-concept compartmentalization (Campbell, Assanand, et al., 2000; Showers, 1992; Showers, Abramson, & Hogan, 1998). In support of the distinction between the two constructs, Campbell, Assanand, et al. (2003) found self-complexity was not related to self-concept compartmentalization (average $r = -.07$). Showers et al. (1998) also reported a near-zero correlation between these two constructs at their first assessment session ($r = .03$), but a moderate negative correlation at the second session ($r = -.33$). Moreover, self-complexity and self-concept fragmentation are often confused with each other. Although as Donahue et al. (1993) pointed out, self-complexity and self-concept fragmentation are “quite different both in how they are conceptualized and in the nature of the relation with adjustment” (p. 844), some researchers occasionally use the two terms interchangeably (e.g., Brown & Rafaeli-Mor, 2001, cited in Koch & Shepperd, 2004; Halberstadt, Niedenthal, & Setterlund, 1996; Jordan & Cole, 1996).

Before we can better understand the relationship among these variables through empirical studies, we need to know how these self-structural variables are measured. To measure these variables, most studies have used a statistic calculated from two-mode

two-way (aspect-trait) matrix data. Usually, these matrix data were obtained in one of the two ways: sorting a list of traits into different groups to represent different self-aspects (e.g., Campbell, Assnand, et al., 2003; Campbell, Chew, & Scratchley, 1991; Dixon & Baumeister, 1991; Hershberger, 1990; Kalthoff & Neimeyer, 1993; Linville, 1985, 1987; Niedenthal, Setterlund, & Wherry, 1992; Rafaeli-Mor, Gotlib, & Revelle, 1999; Showers, 1992; Showers et al., 1998; Woolfolk, Novalany, Gara, Allen, & Polino, 1995, Studies 1, 2, 3, 5), or rating the application of a list of traits to different aspects on a Likert type scale (e.g., Donahue et al., 1993; Gara et al., 1993; Woolfolk et al., 1999; Woolfolk et al., 1995, Study 6). For example, to measure self-complexity, Linville (1987) asked participants to sort a list of 33 traits into groups to represent different aspects of their life (sorting method), while Donahue et al. (1993) required participants to rate the degree to which a list of 60 traits were descriptive of five personal roles to assess self-concept fragmentation (rating method).

Based on the aspect-trait matrix data, a statistic was calculated to indicate a self-structural variable. For example, Linville (1985, 1987) used the H statistic to indicate self-complexity; Gara and Woolfolk (e.g., Gara et al., 1993; Woolfolk et al., 1999) used the HICLAS attribute class number to indicate self-complexity; Showers (1992) used the $Phi (\phi)$ statistic to indicate the degree to which the positive and negative traits are sorted into separate groups—self-concept compartmentalization; and Donahue et al. (1993) conducted factor analysis and adopted the remaining percentage variance after subtracting the portion explained by the first principal component from 1 to indicate self-concept fragmentation. This approach to obtaining these measures is implicit in nature because it infers from the persons' data about their self-structural characteristic,

rather than asks participants to state it. These measurements are based on the assumption that the participants cannot organize their self-aspects about their relationships into an explicit system (see Rosenberg, 1977).

The current study was designed to improve our understanding of the relationships among different self-structural variables and further their conceptual understanding by exploring the associations among six self-structural measures based on trait-sorting data. Linville's self-complexity has obtained relatively the most attention in this field but research into this variable has largely been handicapped by measurement problems. So the different measures of self-complexity are the particular concern of the current study. The six self-structural measures examined here were all previously calculated from aspects by traits matrix data: (1) the H statistic of self-complexity (Linville, 1985, 1987), the two components of H —(2) the number of self-aspects (NASPECTS) and (3) the overlap among self-aspects (OL) in terms of the traits describing them (Rafaeli-Mor et al., 1999), (4) the hierarchical attribute class number (NCLASSES, Gara et al., 1993), (5) the average inter-aspect correlation Φ among different self-aspects in terms of the traits describing them (PHI_CORR), and (6) the self-concept compartmentalization Φ coefficient (COMP_PHI) (Showers, 1992). Each of these measures is described below.

The Self-Complexity Measure H and its Two Components

Linville (1985) conceptualized self-complexity as a “function of two things: the number of aspects that one uses to cognitively organize knowledge about the self, and the degree of relatedness of these aspects” (p. 97). Thus, people may differ in both the number of aspects, and the degree of relatedness among these aspects. Although these differences may result from the number of actual social roles and the differences among

these actual roles, Linville addressed the cognitive nature of self-complexity: it is about the number of aspects people use in thinking about the self and the way they cognitively organize the relationship among roles. Also, “greater self-complexity involves representing the self in terms of a greater number of cognitive self-aspects and maintaining greater distinctions among self-aspects” (Linville, 1987, p. 663).

Linville (1987) used the trait-sorting task to measure self-complexity. In this task, participants were supplied with 33 cards with a feature in each card, such as ‘individualistic’, ‘organized’, etc. Their task was to sort these cards into groups, each group representing one aspect of the self. The number of both self-aspects and the traits in each group was decided by participants. If a trait was applicable to more than one group, participants could use it repeatedly. Therefore there could be some overlap among different groups in terms of the traits describing them. Based on the trait sort, Linville adopted the statistic H from information theory (Attneave, 1959; Scott, 1969; Scott, Osgood, & Peterson, 1979) to operationalize self-complexity. H is calculated in the following way:

$$H = \log_2^n - (\sum n_i \log_2^{n_i}) / n$$

Wherein, n is the total number of traits (33 in Linville’s case), n_i is the number of traits that appear in a particular group combination ($n = \sum n_i$), and $i = 1, \dots, 2^k$, where k is the number of self-aspect groups. A group combination refers to traits uniquely associated with a specific combination of self-aspects. For example, if a person forms two groups, a given trait may fall into one of four possible group combinations: 1, 2, 1-2, or no group (those traits not used at all in the sorting task).

Linville noted that the H score can be interpreted as the minimal number of independent binary attributes underlying a person's feature sort about the self, and it does not require the assumption that people think about themselves in terms of independent binary attributes. "Thus high self-complexity results from having a large number of self-aspects that are non-redundant in terms of the features that describe them. Low self-complexity results either from having few self-aspects or from having many self-aspects that are highly redundant in terms of the features that describe them" (Linville, 1987, p. 666). In other words, the greater the number of self-aspects created and the less redundancy (or overlap) of the features across these self-aspects, the greater is the H score. Therefore, the H measure was presumed to be a combined indicator of both the number and the distinction of self-aspects.

If this is the case, the H statistic should be positively related to the number of self-aspects, and negatively related to the overlap among self-aspects. However, some researchers have found that the relationship between overlap and H is contrary to Linville's expectation. Rafaeli-Mor et al. (1999) analyzed the relationship of the H statistic to the two indicators: quantity of self-aspects and overlap of traits among them. The number of aspects (NASPECTS) was operationalized simply as the number of self-aspect groups formed by participants in the trait-sorting task. Based on the asymmetric similarity relation of Tversky (1977), they used the following formula to compute the overlap among these self-aspects (OL):

$$OL = \sum_i (\sum_j C_{ij} / T_i) / k * (k - 1)$$

Wherein C is the number of common traits in the i_{th} and j_{th} aspects; T is the total number of traits in the i_{th} referent aspect; k is the total number of self-aspect groups in a person's sort; i and j vary from 1 to k (i and j unequal).

Rafaeli-Mor et al. (1999) found that H was positively correlated with both NASPECTS ($r = .71$) and OL ($r = .24$), and the two components were negatively correlated with each other ($r = -.21$). The correlation between H and NASPECTS was similar to that ($r = .72$) reported by Linville (1987). However, the correlation between H and the other component, OL, was contradictory to Linville's prediction. Because the weak negative correlation between NASPECTS and OL was consistent with the hypothesis of Linville's model, Rafaeli-Mor et al. suggested that what was problematic was not the model itself, but the measurement of self-complexity. A recent simulation study (Luo, Watkins, & Lam, 2007) found that the relationship between H and OL was not linear, but like an inverted U curve. In effect, as Locke (2003) pointed out " H doesn't measure differences between roles, and therefore is unlikely to predict spillover" (p. 276). If we take the overlap of traits as a measure of spillover, H is not monotonically related to the overlap.

To resolve this problem in the H measure, some researchers suggested that in future studies the two components should be measured separately, which may be more informative than the use of only one single statistic, H (Lutz & Ross, 2003; Rafaeli-Mor et al., 1999; Rafaeli-Mor & Steinberg, 2002). In particular, some researchers posited that the overlap should reflect the integrity of self-structure, rather than a differentiation variable (Lutz & Ross, 2003; Rafaeli-Mor & Steinberg, 2002).

The Hierarchical Attribute Class Number (NCLASSES)

Some researchers (e.g., Gara et al., 1993; Woolfolk et al., 1999; Woolfolk et al., 1995) used another statistic, the hierarchical attribute class number to indicate self-complexity. In order to gather data, usually participants were asked to characterize several self-aspects preset by researchers using their own language. By aggregating and randomly ranking the words that each participant generated, investigators constructed an attribute list for each participant separately. Then, participants would rate each self-aspect for each attribute (item) in their own list on a 3-point scale (0 = item did not apply, 1 = item applied to a noticeable degree, and 2 = item applied to an extreme degree). The ratings of each participant were formed into an aspects-by-attributes matrix and based on the patterns of attribute co-occurrence across different self-aspects, the traits were partitioned into various classes in a hierarchy by using a clustering program, HICLAS (DeBoeck & Rosenberg, 1988). The index of self-complexity is the number of attribute classes (NCLASSES) in a hierarchy: the larger the number of attribute classes, the greater is the complexity of the self-structure.

As reported by Luo et al. (2007), in effect, when a HICLAS hierarchy can completely represent an observed aspects-by-traits matrix, the HICLAS attribute classes are the group combinations which include endorsed traits in the calculation of H . The more super-ordinate the attribute class (group combination) in a hierarchy, the more aspects are the traits in this class applicable to. For example, if there are only three groups g_1 , g_2 , and g_3 formed, the combination 1-2-3 formed by traits repeatedly used in all the three groups is the most super-ordinate attribute class and the traits in this class can be used to describe all the three groups; the combinations 1-2, 1-3 and 2-3 with traits

repeatedly used in both g1 and g2, g1 and g3, and g2 and g3, respectively, will be in lower classes, and the traits in these classes can only be used to describe only two groups. However, the H statistic is not equivalent to the number of hierarchical attribute classes, because even if the number of HICLAS attribute classes is the same for two individuals, H is also affected by the distributional uniformity of the n traits across these classes.

The Average Inter-Aspect Correlation Phi (PHI-CORR)

The average inter-aspect correlation among different self-aspects has been used to measure self-concept fragmentation. Self-concept fragmentation was defined as “the degree to which an individual’s self is variable or consistent across personally important roles” (Donahue et al., 1993, p. 834). To measure self-concept fragmentation, Donahue et al. (1993) asked participants to rate, in each of five different social roles (friend, romantic partner, son or daughter, student, and worker), how descriptive 60 given traits were of them. The score of self-concept fragmentation was computed for each person. First, they correlated the 60 ratings for each possible pairing of the five roles, and then they factor-analyzed the correlations. The score of self-concept fragmentation was the remaining percentage variance after subtracting the portion explained by the first principal component from 100 percent.

The average inter-aspect correlation can be taken as the opposite of Donahue’s index of self-concept fragmentation. The association between the average inter-aspect correlation R and the Eigenvalue of the first principal component E can be shown by the formula $R = (E - 1) / (N - 1)$, where N is the number of the aspects in the correlation matrix (Donahue et al., 1993). Therefore, R can be used to replace E to indicate the

consistency of personality characteristics across different roles. In fact, some researchers have used the average inter-aspect correlation among self aspects to signify the extent to which a participant’s self-dimensions were integrated—self-consistency (e.g., Sheldon, Ryan, Rawsthorne, & Ilardi, 1997; Suh, 2002), or conversely, the degree to which the self is fragmented—self-concept fragmentation (e.g., Campbell, Assanand, et al., 2003; Campbell, Chew, et al., 1991).

Because the current study used the trait-sorting method, instead of the rating method to gather data, the entries in the aspect-trait matrix were “0, 1” data, and thus the average inter-aspect correlation *Phi* (PHI_CORR) was calculated.

Self-Concept Compartmentalization Phi

Compartmentalization refers to “the tendency that people organize positive and negative knowledge about the self into separate, uniformly valenced categories” (Showers, 1992, p. 1036). The score of self-concept compartmentalization was obtained from the trait-sorting task. Based on the trait sorts of each participant, the *Phi* (ϕ) statistic was calculated by using the following formula to indicate the degree to which the positive and negative traits are sorted into separate groups.

$$\phi = \sqrt{\frac{\chi^2}{N}}$$

Here, N is the total number of traits endorsed in all groups by each individual in the trait-sorting subtask (including the repeated). *Phi* ranges from 0 to 1, with 0 signifying a perfectly random sort and 1 a perfectly compartmentalized sort (Showers, 1992).

In order to clarify the measurement of self-structural variables and to advance our conceptual understanding of these self-process variables, the current study examined how these six self-structural measures are related to each other.

Method

Two hundred and fifty four freshman college students from two universities in Mainland China were invited to complete a trait-sorting task. The participants were aged from 16 to 22 years, with a mean of 19.33 ($SD = .96$). Of these 110 were males (43.3%) and 144 females (56.7%).

The trait-sorting task is similar to Linville's trait-sorting task except for modifications in two aspects. First, in this task, 44 traits including 22 positives and 22 negatives (Linville, 1985, 1987, used 33 traits with a 2:1 ratio of positive to negative traits) were supplied so that participants could have more negative traits to form groups if necessary. The 44 traits were obtained by a pretest procedure which required participants to write at least 12 adjectives to describe their typical characteristics. Then the 44 traits were selected on the basis of the frequency, the valence, and the correspondence of each word with the big five personality factors (Costa & McCrae, 1992)².

Second, the trait-sorting task was administered on personal computers. After providing demographic information, participants were shown an interface with the instruction of the trait-sorting task. Below the instruction window was the window-based interface of the trait-sorting task. On the left-hand side was a column for all the traits to be sorted. On the right-hand side, there were 15 boxes for sorting traits into groups, displayed in three rows with 5 boxes in each row. Participants were instructed to select

the traits in the trait column and move them into a box on the right-hand side to describe each self-aspect group by clicking a button beside each box. Then they needed to enter a name for each group below each box. If they wanted to delete a trait already in a box, they could click another button beside each box to remove it. For the ease of participants to complete this sorting task, we wanted participants to finish all their sorting on just one interface, so all the 15 boxes were shown on the same window interface. The maximum, 15, was decided because the largest number of self-generated groups was around 12 in the literature. For example, Linville (1987) used 33 traits in her research and obtained 3 to 12 self-aspects. In the study of Rafaeli-Mor et al. (1999), also 44 traits were used in the trait-sorting task. The mean number of groups was 5.74 and the standard deviation was 2.10, which was similar to the statistics reported by Linville (1987). In the present study, the largest number of the groups formed was 13, and thus in reality the maximum 15 seemed to be large enough for participants in this study to form as many groups as they wanted.

By using this computer program, the “0, 1” aspect-trait matrix data saved in a file called `sort.dat` were obtained for each participant. This `sort.dat` file included four parts of data: the identification information of each participant, the total number of traits supplied, the number of groups, and the “0, 1” sort matrix. Based on the matrix data, separate programs were used to calculate each self-structural measure. Nielsen’s (1996) H-Comp program was used to compute H . The overlap (OL), the hierarchical attribute class number (NCLASSES), the average inter-aspect correlation Φ (PHI_CORR), and self-concept compartmentalization Φ (COMP_PHI) were all calculated by computer programs designed by the first author. Among these, the program used to calculate the

hierarchical attribute class number (NCLASSES) was based on the most updated version (personal communication with Eva Ceulemans, 2006) of the HICLAS program (DeBoeck & Rosenberg, 1988). The NCLASSES program used in the current study took the number of groups generated as the highest rank to obtain a complete representation of the original sorting data, and could count the total number of attribute classes directly.

Results

Among the 254 cases, two were deleted because they showed extreme values on PHI_CORR (with values more than 3 box lengths from the upper or lower edge of the box plot of PHI_CORR). The distributional skewness and kurtosis statistics of all the six self-structural variables with and without these two extreme cases are shown in Appendix A. It can be seen that after deleting the two cases, the kurtosis index of overlap and the average inter-aspect correlation *Phi* was reduced dramatically.

With the remaining 252 cases, the number of self-aspects ranged from 2 to 13 with a mean of 5.72 ($SD = 1.82$), of which two examples are shown in Appendix B; overlap ranged from .00 to .62, with a mean of .18 ($SD = .13$); *H* ranged from .53 to 5.19, with a mean of 2.78 ($SD = .85$); the number of hierarchical attribute classes ranged from 2 to 39 with a mean of 15.06 ($SD = 7.19$); the average inter-aspect correlation *Phi* ranged from -.33 to .36 with a mean of .02 ($SD = .10$); and the self-concept compartmentalization *Phi* ranged from 0 to 1 with a mean of .58 ($SD = .20$).

Despite the skewness and kurtosis values being all less than about 1.00 after deleting the two extreme cases, further Kolmogorov-Smirnov tests showed that only two of the six variables (*H* and COMP_PHI) were normally distributed. Therefore, in the following

correlational analysis, the more conservative Spearman correlation coefficients were computed.

Table 1 shows the correlations among the six self-structural variables. There was a very high correlation between H and NCLASSES ($r_s = .92$). The relationship between H and NCLASSES is clearly shown in Figure 1 (a). At each number of hierarchical attribute classes, the H values can be different because H is also affected by the distributional uniformity of the traits across all the classes (see Luo et al., 2007). However, in general, there is a clear linear relationship between the two self-complexity measures. Both H ($r_s = .75$) and NCLASSES ($r_s = .89$) were also highly correlated with NASPECTS. Figures 1 (b) and (c) show the linear relationships between the two measures and the number of self-aspects.

<Insert Table 1 about here>

There was a high correlation ($r_s = .87$) between overlap and PHI_CORR as shown in Table 1 and Figure 1 (d). As shown in a simulation study by Luo et al. (2007), there was not a necessarily high correlation between overlap and PHI_CORR from a purely statistical perspective because when PHI_CORR is fixed OL can vary according to the proportion of the traits adopted to form groups. The high correlation found in this study, however, indicated that PHI_CORR would increase as there were more trait redundancies among different aspects (OL) when the total number of traits supplied in the trait-sorting task was fixed.

<Insert Figure 1 about here>

Figures 2 (a) and (b) portray the relationship of OL to both H ($r_s = .43$) and NCLASSES ($r_s = .32$), respectively. In general, the relationship was like an inverted U curve: when OL was less than about .20, both H and NCLASSES tended to increase when OL increased, but when OL was larger, both H and NCLASSES tended to decrease when OL increased. Curve estimation showed a quadratic model ($H = .91 \text{ OL} - .54 \text{ OL}^2$, $R^2 = .19$, $p < .001$; $\text{NCLASSES} = .86 \text{ OL} - .61 \text{ OL}^2$, $R^2 = .13$, $p < .001$) fitted the data significantly better than a linear model ($H = .40 \text{ OL}$, $R^2 = .16$, $p < .001$; $\text{NCLASSES} = .29 \text{ OL}$, $R^2 = .09$, $p < .001$) in both cases. However, because a relatively large portion of OL values were below .20 ($M = .18$) as shown in Figures 2 (a) and (b), there was a positive relationship of OL to both H and NCLASSES. As shown in Table 1 and Figures 2 (c) and (d), PHI_CORR was also positively but more slightly correlated with both H ($r_s = .20$) and NCLASSES ($r_s = .23$) because H and NCLASSES were more directly influenced by overlap than PHI_CORR. The number of self-aspects was not correlated with either OL or PHI_CORR.

<Insert Figure 2 about here>

As shown in Figure 3, the self-concept compartmentalization measure COMP_PHI was not significantly correlated with the number of self-aspects. However, COMP_PHI was negatively correlated with both OL ($r_s = -.50$) and PHI_CORR ($r_s = -.41$), which indicated that participants who tended to put positive and negative traits into separate

categories also tended to use less repeated traits across different self-aspects. Maybe because H had a slightly higher correlation with OL than NCLASSES, there was also a slight but significant negative relationship of COMP_PHI with H , but not with NCLASSES.

<Insert Figure 3 about here>

Discussion

Previous research on the structural features of the self used a number of idiosyncratic and implicit measures which have seldom been related to each other. Unfortunately, this has led to inconsistent findings in the literature, especially in the field of self-complexity as highlighted by the meta-analyses by Rafaeli-Mor and Steinberg (2002), and Koch and Shepperd (2004). Although these implicit nontransparent measures may be potentially advantageous in measuring structural variables of the self, what these measures actually tap and how they relate to each other need to be demonstrated. This research was designed to clarify the relationships between the most commonly used measures in this area and further to improve our understanding of their conceptual meanings. Hopefully, clarification of this issue can lead to more productive research into the dynamic nature of the processing of self-conceptions.

In this paper, six self-structural measures were calculated. The H statistic (H), the hierarchical attribute class number (NCLASSES), the number of self-aspects (NASPECTS) and the overlap (OL) among self-aspects have usually been used to indicate self-complexity or its components; the average inter-aspect correlation Phi

(PHI_CORR) is a way to index self-consistency or self-concept fragmentation; the self-concept compartmentalization *Phi* (COMP_PHI) is a measure of the separation of positive and negative traits in the self-structure. Based on empirical trait-sorting data of 252 Chinese freshmen, the following relationships were found: *H* was highly correlated with the hierarchical attribute class number, and overlap was highly correlated with the average inter-aspect correlation *Phi*; both *H* and the hierarchical attribute class number were highly correlated with the number of self-aspects; although *H* and the hierarchical class number were positively and slightly correlated with overlap and more slightly with the average inter-aspect correlation, the relationships were not simply linear, but more like an inverted U curve; self-concept compartmentalization *Phi* was negatively correlated with overlap and the average inter-aspect correlation, and it was also slightly and negatively correlated with the *H* statistic.

The findings obtained in this study have a number of important implications for future studies in the field of self-structure:

1. As a measure of self-complexity, although the *H* statistic and hierarchical attribute class number are not equivalent, they are highly correlated with each other. Both of these measures can be used to indicate how many unique trait classes are formed with the traits in each class describing the same self-aspect. Also, both are affected by the number of self-aspects and the overlap among self-aspects. Therefore, studies using the *H* statistic as a measure of self-complexity are comparable with those using the hierarchical attribute class number to indicate self-complexity. However, the two measures are not completely equivalent because compared with the hierarchical attribute class

number the H statistic is also influenced by the distributional uniformity of traits across different group combinations or classes.

2. When measuring self-complexity by the statistic H or the hierarchical attribute class number, the influence of the number of self-aspects should be taken into account. It was found in this study that both H and the hierarchical attribute class number were highly correlated with the number of self-aspects. The high correlation between H and the number of self-aspects has also been reported in several studies. For example, in Linville's (1985) Study 1, $r = .69$, in Study 2, $r = .65$; in Linville's (1987) paper, $r = .72$; in Rafaeli-Mor et al.'s (1999) research, $r = 0.71$; and in McConnell et al.'s (2005) study, the correlations rs ranged from .85 to .89.

A related issue is whether utilizing self-aspects generated by participants or preset by researchers may lead to substantial differences in the H value.

However, no matter whether the trait sorting or rating method is used, some studies measured self-complexity by asking participants to generate their own self-aspects (e.g., Hershberger, 1990; Kalthoff & Neimeyer, 1993; Linville, 1982, 1985, 1987; Morgan & Janoff-Bulman, 1994; Salovey, 1992; Showers et al., 1998), while others by presetting the self-aspects (e.g., Gara et al., 1993; Jordan & Cole, 1996; Locke, 2002; Woolfolk, Gara, Allen, & Beaver, 2004; Woolfolk et al., 1999). Thus, whether self-aspects are preset may be one of the reasons to explain why various studies examining self-complexity obtained inconsistent results (for reviews, see Koch & Shepperd, 2004; Rafaeli-Mor & Steinberg, 2002). According to Linville's conceptualization of self-complexity,

high self-complexity involves both a larger number of self-aspects and larger distinctions among self-aspects. If the aim is to measure the self-complexity as conceptualized by Linville (1985, 1987), participants should be allowed to decide the number of self-aspects by themselves.

Not only does the number of self-aspects or self-dimensions vary across individuals, but also the actual self-aspects salient to each individual can be different. For example, as shown in Appendix B, consider the two participants who differ in half of their self-aspects: interpersonal relationship, daily life, study, student committee, part-time job and love (Participant 1); study, interpersonal relationship, religious belief, student committee, relationship with family, and entertainment (Participant 2). Therefore, the distinction component of self-complexity proposed by Linville (1985, 1987) should also be measured in terms of the idiosyncratic aspects generated by each participant, rather than the same self-aspects fixed by researchers. In general, the multidimensional self-concept varies in both the number and the specific dimensions across individuals (e.g., Marsh, 1993; Marsh & Hattie, 1996; Marsh & Shavelson, 1985), and thus it is appropriate to measure the structural variables of the self based on individual self-aspects.

3. Overlap of sorting data as measured by the OL statistic (Rafaeli-Mor et al., 1999) may not be an appropriate measure of the distinction component of self-complexity. Some self-complexity researchers (e.g., Jordan & Cole, 1996; Linville, 1987) took it for granted that high overlap among different self-aspects will lead to a high H value. Based on empirical data, the current study found that

the relationship of overlap to both H and the hierarchical attribute class number was like an inverted U curve. As shown in a simulation study by Luo et al. (2007), completely random sorting of the traits (50 percent of all the traits supplied are adopted in each group. In conjunction with that 50 percent of the traits in each group are overlapped with the traits in any other group) will lead to the maximum of the H value. Thus, as argued by some researchers (e.g., Locke, 2003; Rafaeli-Mor et al., 1999; Rafaeli-Mor & Steinberg, 2002), the H statistic cannot appropriately reflect the spill-over mechanism underlying self-complexity.

Because in the trait-sorting task the overlap value was relatively small ($M = .18$), there was a positive correlation between H or the hierarchical attribute class number and overlap. It is reasonable to infer that when there is a shorter list of more relevant traits, a negative relationship is likely to be found between OL and H . In that case, can we use low overlap to indicate high distinction? As noted by Koch and Shepperd (2004), the possession of some traits in some roles or situations and other traits in other roles or situations may not truly represent the meaning of high cognitive distinction inherent in the conceptualization of self-complexity. From this study, we also found a high correlation between overlap and the average inter-aspect correlation Φ . The latter is often used to indicate Donahue et al.'s (1993) self-concept fragmentation: the higher the correlation, the lower is the remaining variance across self-aspects and thus the lower is the self-concept fragmentation. Therefore it seems that overlap is better used to measure self-concept fragmentation, rather than the distinction component of

self-complexity.

However, it should be noted that the trait-sorting task used in this research and the trait-rating task used by Donahue et al. (1993) have different requirements: in the trait-sorting task, participants need to form their self-aspects by using a list of traits, while in the trait-rating task, participants need to assess the application of each trait in a list to some self-aspects. More specifically, in the trait-sorting task participants may only use the traits which are very characteristic of each self-aspect to describe it, while in the trait-rating task participants just need to rate the degree to which each trait is applicable to each self-aspect. Therefore, the cognitive processes underlying these two tasks may be different, and thus it still cannot be conclusively stated that overlap or the average inter-aspect correlation obtained in the trait-sorting task is an appropriate measure of Donahue et al.'s (1993) self-concept fragmentation.

4. The high self-concept compartmentalization *Phi* partly measures low overlap among different self-aspects. A medium-sized negative correlation ($r = -.49$) was found between self-concept compartmentalization *Phi* and the overlap among self-aspects. Therefore, about 25 percent of the variance in the compartmentalization *Phi* can be accounted for by the overlap among self-aspects. This indicates that people who organize their positive and negative traits separately into different groups may also show less overlap among their whole self-structure in terms of the traits. As discussed above, the high overlap was also highly correlated with the average inter-aspect correlation *Phi*, and actually the compartmentalization *Phi* was also negatively correlated with the average

inter-aspect correlation *Phi* ($r = -.36$). Does a high compartmentalization *Phi* also mean a relatively high self-concept fragmentation? Because we cannot conclude that the low overlap or the average inter-aspect correlation obtained in the trait-sorting task measures Donahue's high self-concept fragmentation, we cannot have a sure answer to this question either. However, in future research, it seems necessary to differentiate those participants with both high compartmentalization and high overlap from those with high compartmentalization but low overlap to improve our understanding about the structural variable of self-concept compartmentalization.

In sum, the current study attempted to clarify the relationships among six structural measures in the field of the self. The results indicate that the self-complexity measure *H* is similar to the hierarchical attribute class number; overlap across self-aspects is similar to the average inter-aspect correlation which may be used to indicate the degree of self-concept fragmentation; *H* and the hierarchical attribute class number are highly affected by the number of self-aspects, while the relationships of the former two measures to overlap are like an inverted U curve, which is contradictory to Linville's prediction; the variance of self-concept compartmentalization *Phi* can partly be accounted for by overlap and the average inter-aspect correlation. From a measurement perspective, this study reveals the underlying relationships among these six self-structural measures. The results obtained in this study are not only helpful to explain the inconsistent findings reported in the literature of this area, especially of self-complexity, but also hold important implications for future research of self-structural variables. In particular, there is a need for researchers of self-structure to answer the question: how should the

construct of self-complexity be measured most appropriately, especially its distinction component? Rather than using an implicit measure, such as overlap among self-aspects in terms of traits, to infer the spillover process, can we measure this process more explicitly? That is, can we directly ask participants to report their perception of the degree of the spillover? In addition, moderate to high correlations were found in the present study among measures of self-complexity, self-concept fragmentation, and self-concept compartmentalization, which may be due to the same aspects-by-attributes matrix data used to calculate these measures. In future research, these self-structural variables should be better discriminated from both theoretical and measurement perspectives.

It should be noted that there are also some limitations of this study. First, all these self-structural measures considered in the present study were calculated from trait-sorting data. All these measures could be sensitive to the composition of the trait list, and thus it is possible that the relationships among these measures might be susceptible to the traits used despite their representativeness of our sample of participants (also see Showers, 1992). For example, as aforementioned it is possible to find a larger value of overlap and a negative relationship between overlap and H when there is a shorter list of more relevant traits. The compartmentalization Φ and also its relationship to overlap may also depend on the proportion of positive traits in the list. In addition, as discussed above, some of these structural measures were obtained in previous research by asking participants to rate the application of a list of traits to several self-aspects, such as the hierarchical attribute class number to tap self-complexity, and the average inter-aspect correlation to tap self-consistency or self-concept fragmentation. The different

manipulations between the sorting and rating tasks may lead to different cognitive processing and strategies of participants when they take these measures, and thus the conceptual meanings of a same statistic obtained from these two tasks may also differ. Researchers in this area should make sure that the measures of these structural variables inferred from aspects-by-traits matrix data in their studies actually examine the constructs they are aimed to measure.

Second, the data in this study were collected with Chinese college students. The results obtained in this study may not be generalized to participants from other cultures or at different ages. To define their selves, Western people seek to maintain independence from others and attend to their unique inner attributes, while Eastern Asian people pay more attention to harmonious interdependence with others (Markus & Kitayama, 1991; Triandis, 1989). The different construals of the self between Westerners and Eastern Asian people may also lead them to organize their self-knowledge in distinct ways. For instance, it has been found that the self-views of Eastern Asian people are organized less consistently across situations (Campbell, Trapnell et al., 1996; Suh, 2002) than are the self-views of Westerners. In addition, since self-concept is more and more differentiated with age—larger number of self-aspects and smaller correlations among self-aspects (e.g., Fitzgerald, Hattie, & Hughes, 1985; Marsh, 1989, 1993; Marsh & Hocevar, 1985), the results with college students in this study also need to be tested with other age samples. For younger children, for example, the number of self-aspects may well be relatively smaller but the overlap among self-aspects in terms of traits may be relatively larger.

The considerations of potential moderating variables are especially important when we examine the adaptational consequences of self-structural variables. It has been reported that in Eastern Asian cultures the association between self-consistency across situations and well-being is weaker than in Western cultures (Campbell, Trapnell, et al., 1996; Suh, 2002). How about other variables? Specifically, since Eastern Asian people are supposed to be more flexible in response to various situations, is high cognitive differentiation among self-aspects more important for them to maintain global self-esteem and well-being? In light of the theory of each self-structural variable, there are also other moderating factors to be considered when we link self-structural variables with well-being. For example, to test the buffering effect of self-complexity, stressful life events should be taken into account. In the examination of the association between self-compartmentalization and well-being, the relative importance or accessibility of positive or negative self-aspects should be considered.

In addition, as addressed by self researchers (e.g., Marsh & Shavelson, 1985; O'Mara, Marsh, Craven, & Debus, 2006), self-concept is multifaceted in nature: "The structure of self-concept and the relationship between self-concept and other constructs cannot be adequately understood if this multidimensionality is ignored" (Marsh & Shavelson, 1985, p. 122). However, all the self-structural variables concerned in this study are originally defined at a broad or overall level, and thus, they are supposed to be particularly predictive of the overall adaptation level in the long run. Because each self-aspect may differ in its importance and in their relation to other self-aspects in the whole self-structure, domain-specific life events and adaptation level may have distinct impacts on the overall well-being level. A few studies (Cohen, Pane, & Smith, 1997; Smith &

Cohen, 1993) have shown that the relative independence of interpersonal self-aspect with other self-aspects, rather than the overall self-complexity, can buffer the effect of life events in interpersonal area on well-being. More attention should be paid to the multidimensionality of self-concept in future studies of self-structural variables in order to understand the processes of the self.

Footnotes

¹ The term “self-concept differentiation” is somewhat misleading because the word “differentiation” is often used to mean pluralism rather than low integration in the self-structure (Campbell, Assanand, et al., 2003). The current study followed Campbell, Assanand, et al. (2003) by replacing it with the term self-concept fragmentation.

² Except that the frequency and valence of each word were used as standards to select words, all the words were generally categorized into the five personality factors in order to avoid synonymous words in the trait list and to assure the selected words could cover all the five personality types. For more information about the development procedure of the trait list, contact the first author.

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Appendix A

Skewness and Kurtosis Statistics of the Six Self-Structural Variables

	H	NCLASSES	NASPECTS	OL	PHI_CORR	COMP_PHI
original 254 cases						
skewness	.10	.49	.45	1.13	1.08	.02
kurtosis	-.14	.04	.61	2.23	5.99	-.36
252 cases after deleting 2 cases with extreme values on PHI_CORR (-.45 and .73)						
skewness	.09	.49	.45	.80	.70	.01
kurtosis	-.12	.06	.65	.35	1.01	-.34

Appendix B

Examples of Two Participants' Trait Sorts

Participant 1					
interpersonal relationship	daily life	study	student committee	part-time job	love
helpful righteous honest generous easy-going impulsive confident cheerful depressed optimistic thoughtful	playful careless lazy	confused clever serious	active confident harebrained responsible passionate careless serious	serious passionate responsible confident active	sensitive introverted quiet depressed confident inconsistent confused self-indulgent thoughtful serious stubborn
Participant 2					
study	interpersonal relationship	religious belief	student committee	relationship with family	entertainment
honest lazy serious stubborn inconsistent active	optimistic thoughtful aloof helpful righteous responsible inconsistent taciturn cheerful kind	optimistic passionate honest serious persistent	responsible serious harebrained honest inconsistent	introverted depressed pessimistic impatient inconsistent confused cold irritable	impulsive harebrained passionate self-contemptuous

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Table 1

Correlations among the Six Self-Structural Variables

	<i>H</i>	NCLASSES	NASPECTS	OL	PHI_CORR	COMP_PHI
<i>H</i>	1.00	.92***	.75***	.43***	.20**	-.19**
NCLASSES		1.00	.89***	.32***	.23***	-.10
NASPECTS			1.00	.07	.11	.07
OL				1.00	.87***	-.50***
PHI_CORR					1.00	-.41***
COMP_PHI						1.00

Note. *H* = Linville's *H* measure; NCLASSES = number of HICLAS attribute classes; NASPECTS = number of self-aspects (groups); OL = Rafaeli-Mor et al.'s overlap measure; PHI_CORR = average inter-aspect correlation *Phi*; COMP_PHI = Showers' self-concept compartmentalization *Phi*.

** $p < .01$, *** $p < .001$.

Figure Captions

Figure 1.

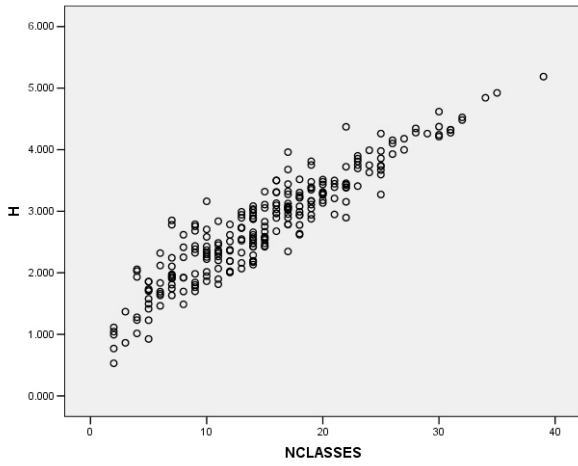
Linear relationships between H , NCLASSES, NASPECTS, OL and PHI_CORR.

Figure 2.

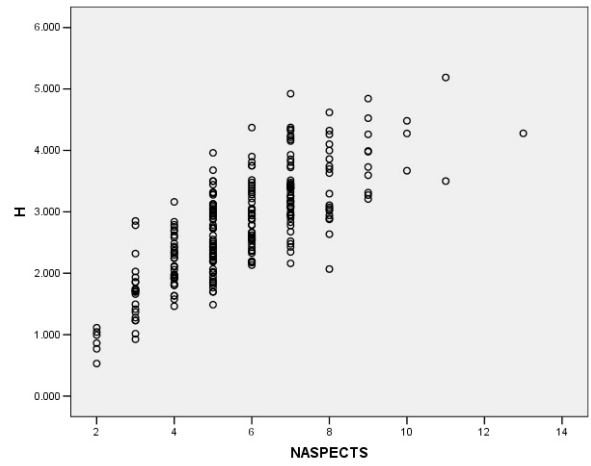
Non-linear relationships between H , NCLASSES, OL and PHI_CORR.

Figure 3.

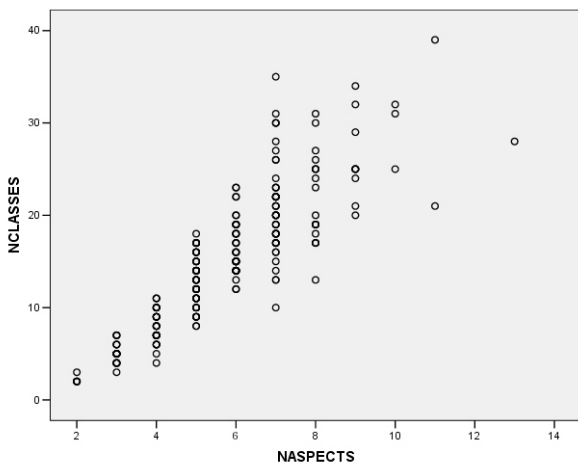
Relationships of COMP_PHI to NASPECTS, OL, PHI_CORR and H .



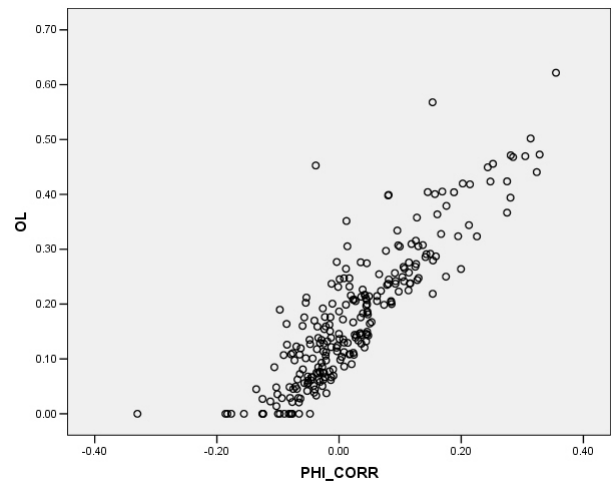
(a) H and NCLASSES



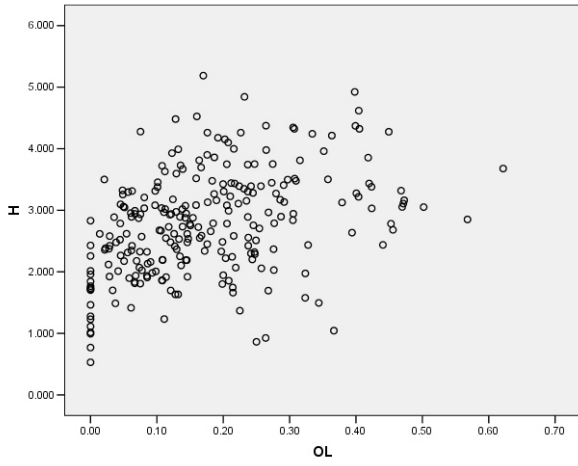
(b) H and NASPECTS



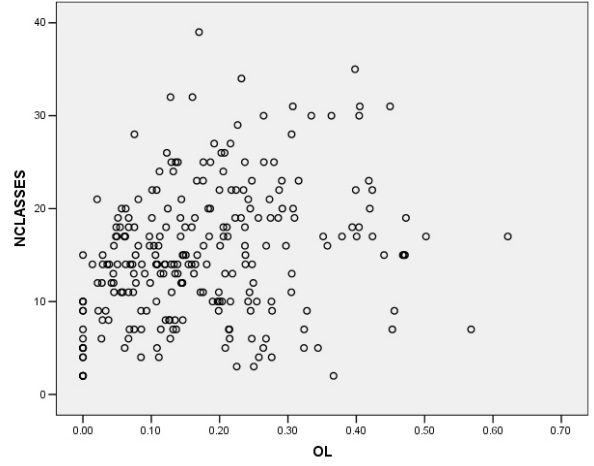
(c) NCLASSES and NASPECTS



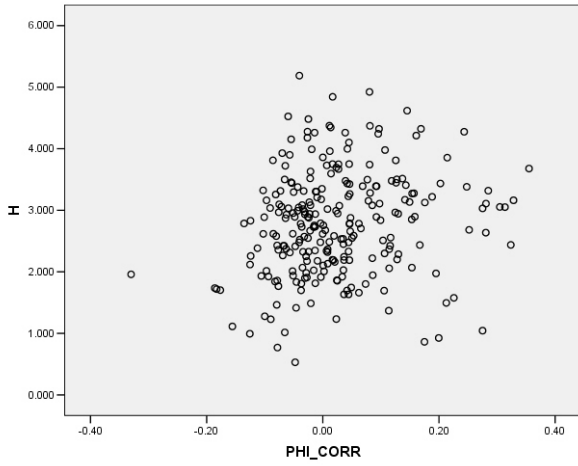
(d) OL and PHI_CORR



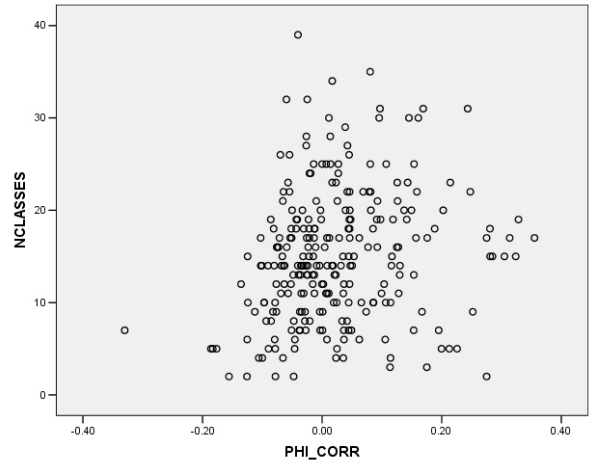
(a) H and OL



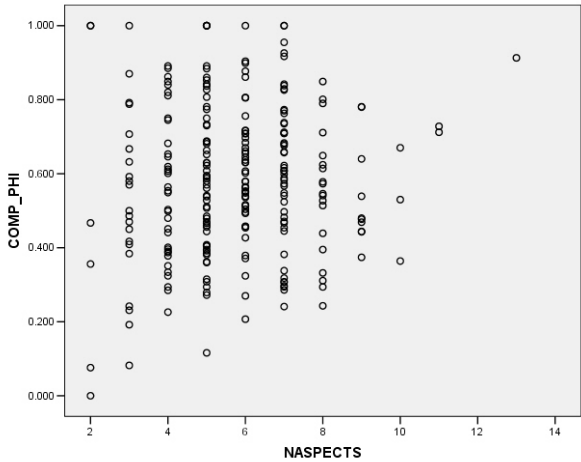
(b) $NCLASSES$ and OL



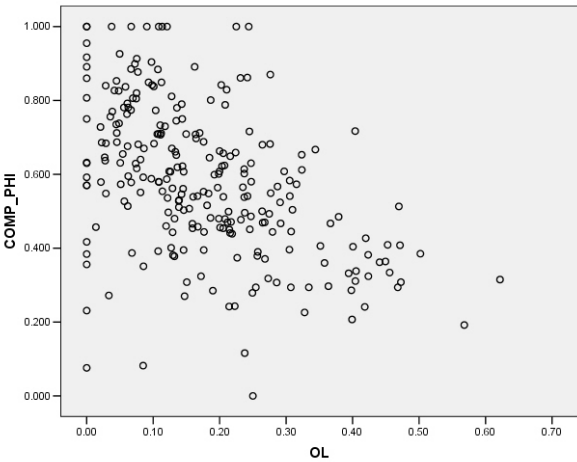
(c) H and PHI_CORR



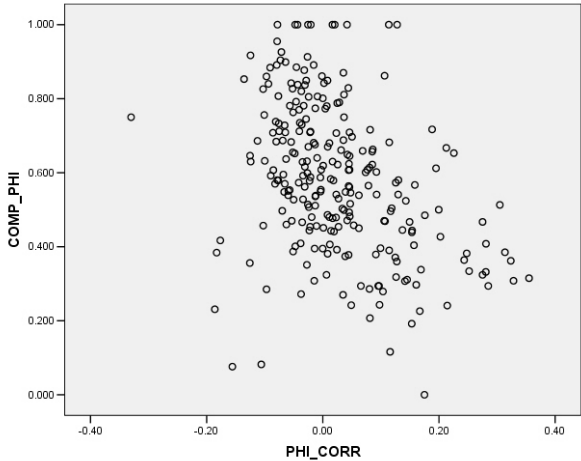
(d) $NCLASSES$ and PHI_CORR



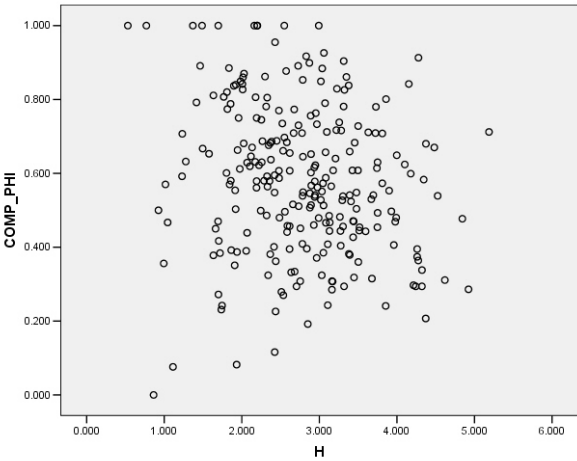
(a) COMP_PHI and NASPECTS



(b) COMP_PHI and OL



(c) COMP_PHI and PHI_CORR



(d) COMP_PHI and *H*