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THE COMPLEXITY OF SELF–COMPLEXITY: AN ASSOCIATED SYSTEMS THEORY APPROACH

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The current work proposed a new measurement of self–complexity based on Carlston's (1994) Associated Systems Theory (AST). AST is a systematic approach to classifying the cognitive representations of social entities and, as such, it provides a rich and theoretically based framework for examining self–concept representation in ways that existent approaches cannot. In the current study, an AST–based measure of self–complexity showed evidence of the buffering effect (i.e., when facing greater stress in their lives, those greater in self–complexity reported greater well–being in terms of fewer physical illnesses and less depression). However, this buffering effect was achieved only when an AST process–based scoring method (i.e., distance in AST space) was used and not when the traditional scoring method (i.e., *H*) was used. Implications of these results for understanding self–concept representation, AST, and their consequences are discussed.

For some time, psychologists have recognized that the self is multifaceted and context–dependent rather than unitary in nature (Baumeister, 1998; Gergen, 1971; Linville & Carlston, 1994). Be-

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cause self–concept plays a fundamental role in self–regulation, social functioning, and the experience of affect (e.g., Baumeister, 1998; Higgins, 1997; Taylor & Brown, 1988), understanding its cognitive representation and the consequences of variability in its structure is extremely important. Accordingly, the current study undertook a new approach to assessing self–concept representation based on Associated Systems Theory (Carlston, 1992, 1994).

SELF–COMPLEXITY

Although the complexity of self–concept representation has been conceptualized in many different ways (for reviews, Rafaeli–Mor & Steinberg, 2002; Woolfolk, Novalany, Gara, Allen, & Polino, 1995), arguably the most influential formulation regarding the link between self–concept representation and well–being has been self–complexity (Linville, 1985, 1987). This line of work is grounded in four assumptions about the self. First, the self is cognitively represented in terms of multiple self–aspects, which correspond to important ways that people think about themselves such as their traits, roles, physical features, social categories, behaviors, abilities, preferences, goals, autobiographical recollections, and relations with others (Linville, 1985). A second assumption is that these self–aspects vary in the affect associated with them.

Third, people differ in the degree of complexity of their self–representations (Linville, 1985), which refers to both the *number* of self–aspects and the degree of *relatedness* of those self–aspects. Specifically, self–complexity increases as the number of self–aspects increases and as the independence of those aspects increases (Linville, 1985; 1987).[1] For example, consider a

1. Throughout this paper, we use the term "self–complexity" to refer to the construct, not the typical way in which the construct has been operationalized. "Self–complexity as defined here is 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" (Linville, 1985, p. 97). "Greater self–complexity entails cognitively organizing self–knowledge in terms of a greater number of self–aspects and maintaining greater distinctions among self–aspects" (Linville, 1987, p. 663). These are the two theoretical components of self–complexity (i.e., number of self aspects and their distinctiveness/independence/(un)relatedness). One should not equate self–complexity as a construct with the approach frequently used in the literature to measure it (i.e., Scott's *H* applied to the results of a trait sorting task).

20–year–old woman who identifies eight self–aspects, two of those being "sorority" and "relationship with boyfriend." Further assume that she thinks of herself in her sorority self–aspect as "well dressed" and "student," but she thinks of herself in her relationship self–aspect as "attractive" and "woman." According to the self–complexity model (Linville, 1985; 1987), this person would be relatively greater in self–complexity because she thinks of herself in terms of a relatively large number of self–aspects (eight) and because there is no redundancy of features comprising those self–aspects (i.e., she uses different attributes in those two domains). This degree of complexity is presumed to affect the *spillover* component of self–complexity. That is, greater self–complexity should minimize the overall impact of affect associated with experiences involving one self–aspect because each self–aspect is composed of relatively unique attributes and because a relatively small proportion of the self will be implicated by feedback about oneself. The fourth and final assumption of this self–complexity model is that overall well–being is a function of the affect and self–appraisal experienced among the different aspects of the self (Linville, 1985).

This self–complexity model has been used frequently for predicting psychological and physiological outcomes associated with the self. For example, Linville (1985) found that less self–complex people experienced more extreme affect and self–appraisal (e.g., more positive after success and more negative after failure)—presumably due to the spillover effect—and exhibited more variability in affect over time (see also Campbell, Chew, & Scratchley, 1991; McConnell & Rydell, 2004). Relatedly, Renaud and McConnell (2002) replicated these mood swing effects and found that those lower in self–complexity had greater difficulty in suppressing thoughts associated with negative academic feedback because being lower in self–complexity made returning to thoughts of their student self–aspect more likely to occur (due to spillover effects).

It has also been argued that self–complexity has important implications for how people deal with life's stressful events. In one influential paper (Linville, 1987), those greater in self–complexity coped better with stressful events (i.e., events likely to lead to stress–related illness or depression) than people who were less self–complex, providing evidence that self–complexity serves a *buffering* function. That is, when experiencing negative life events, being greater in self–complexity can ameliorate the impact of stress.

The above review suggests that self–complexity is not only an intuitively appealing construct, but it is also a good predictor of meaningful psychological and physical outcomes. However, a recent review of self–complexity research concluded that there is not overwhelming support for the buffering hypothesis (Rafaeli–Mor & Steinberg, 2002). Those authors reviewed 24 studies examining the stress–buffering role of self–complexity and found that although seven studies supported the buffering hypothesis, four studies showed results directly opposite to it, and the remainder did not find any stress by self–complexity interaction. Thus, despite its intuitive appeal, self–complexity often fails to reveal the buffering effect. These inconsistent findings suggest that our understanding of self–complexity and its relations to well–being is far from complete. In particular, it is possible that the measurement of self–complexity can be improved.

POTENTIAL LIMITATIONS IN THE MEASUREMENT OF SELF–COMPLEXITY

The most typical approach to measuring self–complexity involves participants placing self–descriptive traits (25–40 have been used in most studies) into groups that describe meaningful aspects of their lives. Thus, each group represents a self–aspect (e.g., student) and is composed of relevant traits (e.g., organized, insecure, competitive) descriptive of that self–aspect. Participants generate as many self–aspects as they wish, and each trait may be used once, more than once, or not at all. These trait sorts are then used to compute a self–complexity score, *H*, which is a measure of differentiation among attributes (i.e., an index of redundant pairings of attributes used in the trait sorting task; see Scott, 1969; for a critique, see Locke, 2003).

Although this trait–sorting method has been the dominant approach to measuring self–complexity (see e.g., Linville, 1987; Woolfolk et al., 1995), it is possible that alternative approaches to measurement might better capture the complexity of the self. Specifically, self–relevant knowledge is presumed to be multidimensional and diverse. Indeed, Linville (1987) points to the richness of the self, including one's roles, relationships, activities, superordinate traits, and evaluations. The traditional self–complexity measurement task, however, asks participants to consider and sort *trait attributes only* (e.g., anxious, outgoing, mature). Perhaps stimulus materials reflecting other important ways that people think about themselves (e.g., roles, relationships, activities, social categories, evaluative and affective descriptors) would more richly capture one's representation of the self and thus predict self–relevant outcomes better. As noted by Niedenthal, Setterlund, and Wherry (1992, p.15):

> Complexity involves both breadth and depth of knowledge. The card–sorting task used to measure self–complexity in this and other studies...measures differentiation (i.e., the number of self–aspects) and integration (i.e., the extent to which aspects share common features). However, these are assessed at only one level of abstraction. Future research should test the self–complexity model using a task for measuring complexity that captures all of its theoretical components.

Although Linville (1985) used *roles* (rather than traits) in one study, no work has simultaneously used a variety of different types of attributes in the self–complexity task.

In addition to providing a broader array of attributes, it is also possible that alternative approaches to self–complexity measurement might better uncover the *relatedness* of self–aspects and therefore better capture the processes underlying the buffering effect. That is, some previous research has been unclear about whether, in addition to the *number* of self–aspects, self–complexity measures assess the *redundancy* or the *relatedness* of the self–aspects. Linville (1985), for example, used both terms interchangeably (p. 98), and no subsequent studies have attempted to clarify this. These two qualities, however, are not identical. Whereas the typical measurement of self–complexity (using *H*) has looked only at *redundancy* of attributes across self–aspects, an alternative approach to measuring self–complexity would ideally allow for an examination of the *relatedness* of attributes within and across self–aspects.

Why distinguish between redundancy and relatedness? Relatedness allows for a finer test of the proposed spillover that is part of the self–complexity model. That is, although the self–complexity model (Linville, 1985; 1987) assumes a spread of general activation within an associative network, it does not speak to how social knowledge is organized and related in memory (other than, presumably, through paired associations; see also, McConnell & Rydell, 2004). Thus, incorporating a richer theoretical framework of knowledge organization for the measurement of self–complexity might allow for process–derived predictions to be considered and tested, thus greatly expanding our understanding of *how* buffering is achieved.

The above review suggests the potential benefits of a new approach to measuring self–complexity that would include a representation framework that allows for the assessment of the rich content of self–aspects (i.e., more than simply traits) while also providing an underlying process account. We propose that one such framework meeting these criteria is Associated Systems Theory (AST). After a brief review of AST, we discuss how it can be leveraged to measure self–complexity in ways that address the aforementioned concerns.

ASSOCIATED SYSTEMS THEORY

AST is a framework developed by Carlston (1992, 1994) as a systematic approach to the cognitive representation of social entities, including the self. As shown in Figure 1, the AST structural model of representation (Carlston, 1994) is based on the assumption that there are different kinds of mental systems that process information: visual, verbal, affective, and action. The characteristic representation for the *visual system* is a visual image of a person's appearance, including physical expressions and mannerisms as well as static features such as height and attractiveness. Words and propositions make up the *verbal system*, which includes personality trait concepts. The *affective system* involves the experience of emotion, and finally the *action system* involves the representation of behaviors. These systems produce four primary and four secondary forms of cognitive representation. The primary forms

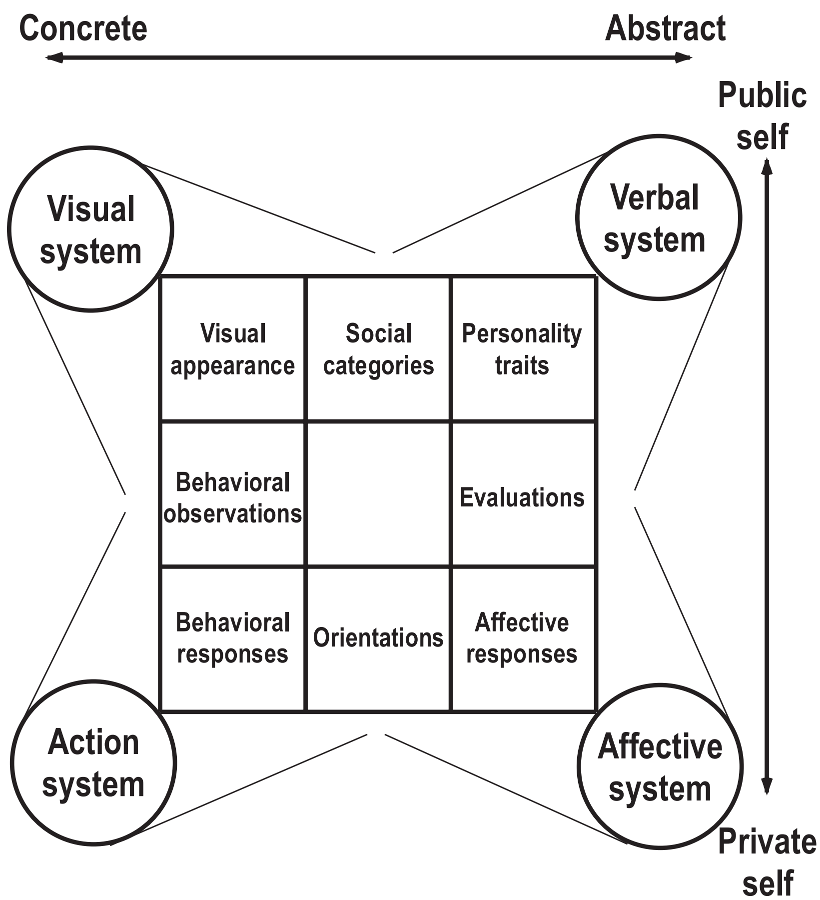

FIGURE 1. Taxonomic representation of the interrelationships among forms of person representation and primary mental systems.

(directly linked to one of the mental systems) are visual appearance (visual system), personality traits (verbal system), affective responses (affective system), and behavioral responses (action system). The secondary forms of representation are produced by combinations of two mental systems: social categories (visual + verbal systems), evaluations (verbal + affective systems), orientations (affective + action systems), and behavioral observations (action + visual systems).

Although the AST model is presented in matrix form giving the appearance of discrete representational cells, there are two underlying, continuous dimensions of representation: *target–reference* versus *self–reference*, and *concreteness* versus *abstraction*. Along the vertical axis of the AST model, the representational forms are organized from characteristics of the person being perceived (target–referent), which are associated primarily with the visual and verbal systems, to attributes of the perceiver (self–referent), which are associated primarily with the action and affective systems. The horizontal axis organizes representations from relatively concrete concepts based on visual appearance or behavioral observations at the far left, to abstract representations independent of any particular time, place, or circumstance in the form of personality traits, evaluations, and affective responses at the far right.

Although Carlston (1994) notes that AST can be applied to self–descriptions, some modification is necessary. That is, although the concrete–abstract dimension (horizontal axis) fits self–descriptions and target–descriptions equally well, the self–target dimension (vertical axis) is more problematic for self–descriptions, where presumably all statements would be associated with the self. In an unpublished study (D. E. Carlston, personal communication, June, 2003), multidimensional scaling techniques revealed that although the concrete–abstract dimension fits self–descriptions well, the vertical dimension is most appropriately conceptualized as *public versus private self*, rather than target versus self referent. Thus, representations near the top row of the taxonomy represent features that are clear to others who view the self (i.e., public self), such as one's appearance, social categories, and personality traits, whereas representations closer to the bottom row capture elements of the self that are not immediately clear to others (i.e., private self), such as orientations toward others and feelings evoked by others. Accordingly, an AST–based approach to measuring self–complexity might use these two dimensions (i.e., concrete–abstract and public self–private self), in addition to the eight primary and secondary forms of representation ("cells"), to classify self–descriptors.

In addition to providing a framework for including multidimensional and varied self attributes (e.g., appearance, evaluations, social categories, behaviors, *as well as* traits), AST can also provide a way to consider the relatedness among self–aspects and their attributes. Specifically, AST postulates that the probability of associative links is greater for representations that are spatially proximate. When a mental system is engaged, representations that relate to it are more likely to be simultaneously activated, and these spatially proximate representations are therefore more likely to become associated with each other. Furthermore, Carlston (1994) notes that representations derived from the same system often have basic features in common, hence the activation of one facilitates the activation of nearby others. In general, and on average, proximal representations should be more strongly associated than more distal representations. Such a process component, we propose, has important implications for the spillover processes presumed to be operating in the buffering theory of self–complexity.

To illustrate this point, recall the earlier example of the woman with the self–aspects sorority (well–dressed, student) and boyfriend (attractive, woman). Presumably, she has relatively greater self–complexity, as traditionally assessed, because there is no *redundancy* in the features comprising these two self–aspects. However, as conceptualized within the processes of the AST framework, there is a great deal of *relatedness* between these two self–aspects. Indeed, these aspects each include one visual appearance attribute (i.e., well–dressed, attractive) and one social category attribute (i.e., student, woman). Because these two self–aspects are composed of the same type of representation forms *and* because these two forms are proximal in AST space (see Figure 1), it is more likely that the activation of one of these self–aspects will result in the activation of the other, with any affect associated with the first spilling over to the second. For example, if her boyfriend compliments her physical attractiveness during a date, her visual representation will be engaged. Moreover, because her sorority self–aspect contains attributes spatially proximate to the visual system, this positive feedback about her visual appearance will spill over to her sorority self–aspect as well. This spatially–proximate spillover should occur even though the particular visual appearance attributes associated with these two self–aspects are not identical (i.e., redundancy), but rather, reside near each other in AST space (i.e., relatedness). It is this aspect of the AST framework that allows for a more refined and process–derived account of the proposed spillover effect. Specifically, in order to reduce spillover, and therefore buffer against negative stress–related outcomes such as depression and illness, an individual's self–aspects should be relatively *isolated* (i.e., not spatially proximate) in AST space.

This analysis suggests the potential utility of AST for providing a new approach to measuring self–complexity that addresses the previously noted limitations in the traditional methods. Specifically, an AST–based approach to self–complexity captures the richness with which people describe themselves by including attributes from throughout AST space rather than solely using traits, and it also provides a process component to account for spillover effects. Finally, it can offer a richer measure of self–complexity derived from this process model that captures relatedness among self–aspects by assessing how isolated they are in AST space. For the above reasons, it is predicted that this new AST–based approach to measuring self–complexity should reveal the buffering effect. Moreover, as elaborated below, it is also expected that an approach to measuring AST–based self–complexity that takes into account this process component (i.e., *relatedness* of self–aspects and their attributes) should be better at revealing the buffering effect than a more simplistic method involving the *redundancy* of attributes (i.e., *H*).

RELATEDNESS VERSUS REDUNDANCY APPROACHES TO SCORING

Within the use of AST–based attributes, we can examine whether a self–complexity index based on relatedness (i.e., based on the process component of AST and operationalized via AST space) is superior to one based on redundancy. Specifically, greater self–complexity under the former approach is defined as the possession of many, isolated self–aspects. This isolation is operationalized by two separate components: greater distance *between* self–aspects (making it more difficult for one self–aspect to activate another) and shorter distances among attributes *within* self–aspects (reducing the range of AST space that any one self–aspect occupies).

Redundancy, on the other hand, will be operationalized via the scoring method used in traditional self–complexity research, *H*, which is defined as the number of independent dimensions underlying the collection of attributes used in the self–aspects. For any number of self–aspects, *N*, there are 2^N categories that represent all possible combinations of groups into which an attribute can be placed. Every attribute belongs to one and only one of these combinations, referred to as unique group combinations (UGCs). The formula for *H* is:

$$H = \log_2 n - (\Sigma_i n_i \log_2 n_i) / n,$$

where *n* is the total number of attributes available for sorting, and n_i is the number of attributes appearing in each UGC. The formula reveals that *H* increases as the number of UGCs increases. In other words, *H* can be considered an index of redundant pairings of attributes used in the sorting. As such, *H* is only a structural measure and cannot fully capture the content or meaning of the attributes nor relations among them (Linville, 1985). In fact, indirect evidence for this comes from consistent findings that *H* and the total number of self–aspects produced are highly correlated (Linville, 1985, 1987, found *r*s ranging from .65 to .72; McConnell et al., 2005, found *r*s ranging from .86 to .90; Woolfolk et al., 1995, found *r*s from .90 to .94 across six studies), suggesting that relatedness between (even redundancy within) self–aspects is not well captured by *H* (see Locke, 2003; Rafaeli–Mor, Gotlib, & Revelle, 1999). Therefore, it is predicted that the relatedness (i.e., distance–based) measure of AST self–complexity will be superior in terms of revealing the buffering effect to the redundancy (i.e., *H*) measure of AST self–complexity.

SUMMARY OF CURRENT STUDY

Based on Linville (1987), we hypothesize that those facing more negative life events (i.e., greater stress) would subsequently report relatively better well–being (i.e., fewer physical symptoms and less depression) when greater in AST–based self–complexity.[2] In addition, we hypothesize that the relatedness approach to scoring self–complexity (i.e., distance in AST space) would fare better than the more traditional redundancy approach (i.e., *H*).

Finally, we would note that in testing the utility of an AST approach to measuring self–complexity, this study represents one of the first empirical tests of AST, and the first published application of AST to the self. Although numerous implications of AST have been discussed on a theoretical level (see Carlston, 1994), empirical tests of AST are few (for exceptions, Claypool & Carlston, 2002; Schleicher & Day, 1998). Thus, in addition to addressing possible limitations in previous approaches to measuring self–complexity, the current work represents a rather novel and substantial test of a broad, but not yet extensively validated, theoretical framework.

METHOD

STIMULUS MATERIALS DEVELOPMENT

Pilot testing was undertaken to develop a set of attributes for the self–complexity sorting task that were representative of AST's visual, verbal, action, and affective systems (previous self–complexity stimulus materials have included only trait descriptors, with the exception of one study solely using role descriptors, Linville, 1985). First, 25 undergraduates at Penn State University (none of whom participated in the primary study) were given open–ended self–description tasks. Second, the most frequently listed self–descriptions were given to three judges trained in AST coding procedures (see Carlston & Sparks, 1992, 1994). These judges classified each descriptor according to which of the nine AST cells it represented (see Table 1 for cell definitions), and they also rated each descriptor along the two continuous AST dimensions hypothe-

2. We also examined whether self–esteem might reveal buffering as well, using Rosenberg's (1965) 10–item scale. Although stress predicted poorer self–esteem overall, self–esteem showed no evidence of buffering (i.e., there was no stress × self–complexity interaction in predicting changes in self–esteem). This finding is consistent with other research (e.g., Campbell et al., 1991; Woolfolk et al., 1995) that has failed to show evidence of buffering for self–esteem.

TABLE 1. AST Attributes Sorted by AST Category

Visual Appearance	Social Categories	Personality Traits
Hair Color	Student	Hard Working
Height	Age	Kind
Body Image	Gender	Friendly
Well–dressed	Academic Class	Funny
Attractive	Political Affiliation	Outgoing
		Shy
		Insecure
Behavioral Observations	**General***	**Evaluations**
I Read	Religious	Likeable
I Drive	Studious	
I Play Musical Instruments	In a Rut	
I Work		
I Play Sports		
Behavioral Responses	**Orientations**	**Affective Responses**
Roommate Relations	Family	I Like/Dislike Animals
Communication with Parents	Significant Other	I Like/Dislike Music
Significant Other Conflict	Self Esteem	I Like/Dislike Penn State**
Meeting New People	Loneliness	I Like/Dislike Schoolwork
	Friends	

Note. *The "General" category of attributes corresponds to the center cell of the AST matrix (see Figure 1); **This item was replaced with "I Like/Dislike Michigan State" in the primary study. Definitions of each category provided to coders were as follows: (a) Visual Appearance: describes a perceptible characteristic of the writer, such as his/her physical appearance or dress, voice, smell, etc.; (b) Social Categories: indicates a social, organizational, professional, political, societal or ethnic group or category to which the writer belongs; (c) Personality Traits: describes the writer's traits, abilities, personality attributes, or personality type; (d) Behavioral Observations: describes the writer's behavior(s), performed alone and/or not performed with or directed toward other people; (e) General: describes the writer's general behavioral attributes, thoughts, attitudes, personal preferences, etc., which do not fit into other categories. Descriptors that clearly incorporate both behavioral and trait qualities fit here; (f) Evaluations: describes the general goodness, badness, or likeability of the writer without conveying information about his/her personality; (g) Behavioral Responses: describes the writer's actual behaviors toward a specific other person (or people); (h) Orientations: describes the nature of the writer's relationship towards or with another person (or people), or the nature of the writer's relationship with him/herself; and (i) Affective Responses: describes the writer's emotional feelings or physical reactions toward a specific other person, people, or things.

sized to underlie self–representation (i.e., concrete–abstract, public–private self) using 9–point scales. These ratings displayed a high level of agreement, with mean intercorrelations between raters of .76 for the concrete–abstract dimension and .77 for the public–private dimension. The final set of descriptors (39 in total; see Table 1) were then chosen such that they both represented frequent responses by participants and were relatively representative of the AST cells, with a stronger emphasis on frequency of report than AST cell representation. To make the specific descriptors generated by these participants applicable to students as a whole, some responses were translated into more generic descriptions. For example, "I have red hair" became "hair color." Additional pilot testing by 77 undergraduates, none of whom participated in the primary studies, revealed that people felt these 39 items could capture the essence of their self–aspects.

PRIMARY STUDY

Participants

At Michigan State University, 110 undergraduates participated in this study for extra credit in their introductory psychology courses. They were run individually at private computer workstations in two sessions (hereafter, Time 1 and Time 2) that took place exactly two weeks apart. Thus, the method was modeled after other self–complexity "buffering" studies that used a prospective design (e.g., Linville, 1987; McConnell et al., 2005; Woolfolk et al., 1995).

AST–Based Self–Complexity Task

Participants completed the attribute sorting task, following a method used by Renaud and McConnell (2002). Using a Windows–based interface, they selected the attributes to be used in each self–aspect from a list of all available attributes, and after they formed each group, they labeled it (e.g., "my student self"). With the exception of the medium and the specific stimulus materials, the method and instructions paralleled those of Linville

(1987). That is, participants were instructed to form groups of attributes that go together, with each group describing a meaningful aspect of their lives. They were told that each group could contain as many or as few attributes as they wished, that they did not have to use each attribute, and that each attribute could be used in more than one group. Participants were told to keep in mind that they were describing themselves while performing this task, not people in general. Further, they were told to continue producing new self–aspects until they felt that all of the important facets of their life were represented.

Several different indexes of self–complexity were computed from the participants' card sorts, including the number of self–aspects generated, *H*, and two distance–based indexes. *H* was computed using the formula previously described, with larger values representing greater AST self–complexity. The computation of the distance–based indexes was slightly more complicated. Recall that three judges had previously coded each attribute according to both which AST cell it represented and where it fell (on a 9–point scale) along the two underlying AST dimensions. Hence, each of the 39 attributes in the sorting task could be represented by *two* sets of Cartesian coordinates (cell and dimension, respectively) according to its location in AST space. First, the AST *cell* coordinates were produced by treating the 3×3 matrix as a coordinate system bounded by (1, 1; behavioral responses) and (3, 3; personality traits). Thus, the origin for these cell coordinates was fixed at the bottom left of the AST matrix shown in Figure 1. Second, assessing each attribute as to where it fell along the two continuous AST dimensions led to a second set of coordinates, with these *x* and *y dimension* coordinates ranging from 1 to 9. The *x* coordinate represented the concrete–abstract dimension, with smaller values indicating more concrete attributes (and larger values, more abstract). The *y* coordinate represented the private–public self dimension, with smaller values indicating more private attributes (and larger values, more public). Both sets of coordinates, cell and dimension, were examined because it was thought that the continuous variable (i.e., dimension coordinates) might provide additional sensitivity lost when considering AST as a 3×3 matrix. These mean coordinates (across the three judges)

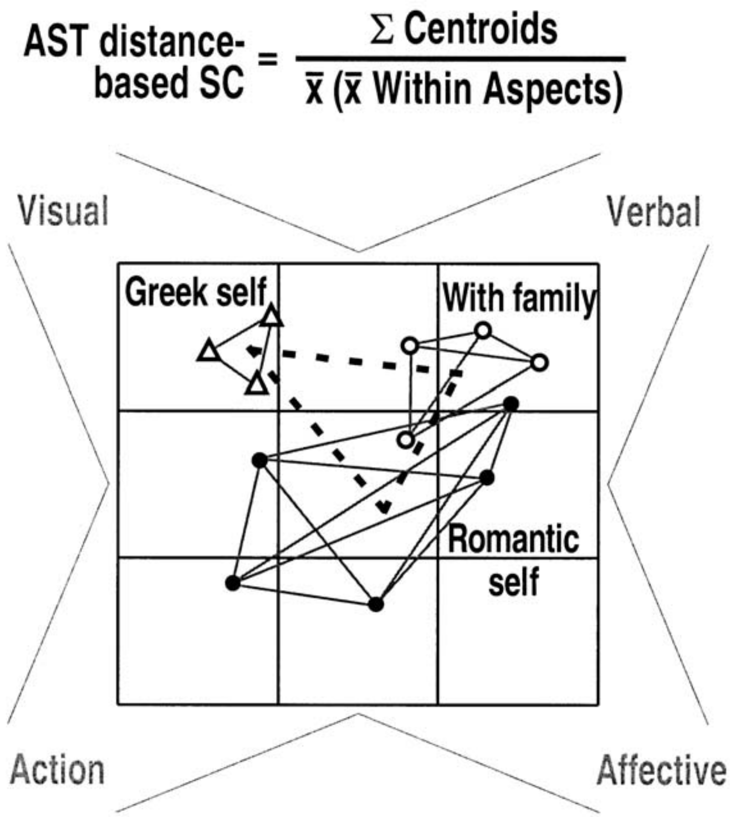

FIGURE 2. Illustration of the components of the AST process-derived self-complexity index for a hypothetical participant with three self-aspects.

were then used to compute the distance between attributes used in participants' card sorts, as discussed below.

Recall that greater relatedness–based AST self–complexity was defined as having a greater number of self–aspects that are relatively *isolated* in AST space. This isolation was operationalized by two separate components: distances *between* self–aspects, and distances among attributes *within* self–aspects. Isolated self–aspects would occur when the distance *between* self–aspects is large and the distance among attributes *within* self–aspects is small. Accordingly, the first component (distance between self–aspects) was placed in the numerator of this index, and the second component (distance within self–aspects) was placed in the denominator. For each participant, distance between self–aspects was computed by first finding the centroid of each self–aspect (i.e., the mean coordinates for all of the attributes in that aspect) and then summing the distances among the centroids of all the self–aspects. The sum (instead of the mean) of these distances was used to reflect the notion that having more selves in general leads to greater complexity. As Figure 2 illustrates, the numerator term would be the sum of the dashed lines (which connect the centroids). Thus, as one possesses more self–aspects with central tendencies located in different portions of AST space, the numerator increases in value (and so too does self–complexity). Distance within self–aspects was computed by taking the mean across self–aspects of the mean distance between all possible pairings of attributes within each aspect. Thus, this "within" term (the denominator) represented the average amount of distance between attributes in the average self–aspect, which in Figure 2, is represented by the mean length of the solid lines.[3]

Stress

A measure of life stresses was included at Time 1 because of the proposed buffering effect of self–complexity. That is, Linville

3. The AST distance–based indexes were actually computed using both Euclidean and city block distance metrics, because it was believed that these two approaches to measuring distance might provide unique information relevant to AST theory (D. E. Carlston, personal communication, June 1998). For example, consider the two descriptors "student" (a social category) and "likeable" (an evaluation). In the AST matrix (see Figure 1), these two descriptors are approximately 1.4 units (i.e., the square root of 2) apart from one another when measured by Euclidean distance (i.e., the diagonal). However, in terms of city block distance, these descriptors are two units apart from each other (i.e., one unit on the concrete–abstract dimension and one unit on the public–private self dimension). Therefore, the city block metric may be more useful in terms of preserving the information about differences on both dimensions. We therefore tested our hypotheses using both the Euclidean and city block metrics, for both the cell and dimension coordinates.

In the end, however, all four distance–based AST indexes (i.e., cell vs. dimension × Euclidean vs. city–block) were highly intercorrelated (*r*s = .88 to .95) and produced the same pattern of results in the regression analyses. Thus, in the interest of clarity and space, we only present data for the Euclidean–dimension index because it provides greater meaningful variability in its measure (vs. cell coordinates) and because Euclidean distance may be more intuitive for readers. It remains theoretically possible that a city–block approach may capture important information that provides additional predictive utility, but in the current study it did not.

(1987) found greater self–complexity to be related to better well–being only following stressful periods in one's life. This results in an interaction between self–complexity and stress in predicting changes in stress–related outcomes (e.g., physical illness, depression). Therefore, the participants in the current study completed a modified version of the College Student Life Events Scale (CSLES; Levine & Perkins, 1980), the same measure employed by Linville (1987). The 137 items of the scale represent life stressors of relevance to college students. For each item, participants indicated whether the event in question (e.g., end of a romantic relationship) had happened to them during the past two weeks, during the past six months (excluding the past two weeks), or not at all. For those events that had occurred, participants rated whether the impact of the event was negative, neutral, or positive. Following Linville (1987), the stress index used in the current study was the sum of only those stressors experienced in the last two weeks that had a negative impact.

Physical Symptoms and Illness

Participants completed the Cohen–Hoberman Inventory of Physical Symptoms (CHIPS; Cohen & Hoberman, 1983) to assess 33 stress–related physical symptoms commonly experienced by college students (e.g., cold, nausea, headache) at Time 1 and Time 2. Participants responded to this inventory on a scale ranging from 0 (*not bothered by the problem*) to 4 (*extremely bothered by the problem*), indicating the extent to which each physical symptom had bothered them in the past two weeks. The sum of each participant's ratings for the 33 items served as the index of physical symptoms for the corresponding session. The scale was reliable both at Time 1 (α=.91) and at Time 2 (α=.93).

Depression

Participants completed the short form of the Beck Depression Inventory (BDI; Beck, Ward, Mendelson, Mock, & Erbaugh, 1961) at Time 1 and at Time 2. The BDI consists of a 13–item scale asking participants to choose one of four statements for each item, reflecting varying levels of depression. Following Beck et al. (1961), each of these statements was assigned points (0 to 3), where larger values indicate greater depression. For example, one item consisted of these four options: (a) I don't feel disappointed in myself (coded as 0); (b) I am disappointed in myself (coded as 1); (c) I am disgusted with myself (coded as 2); and (d) I hate myself (coded as 3). The sum of the responses served as the index of depression at each session, and the scale was reliable both at Time 1 (α=.87) and at Time 2 (α=.93).

Procedure

At Time 1, participants arrived at the lab and were told that the current study was assessing how undergraduates describe themselves. After completing informed consent forms, participants were placed in individual rooms at private computer workstations for the remainder of the experiment. The computer then administered the AST–based self–complexity task, the stress measure, the physical symptoms inventory, and the depression inventory. Exactly two weeks later, participants returned to the lab and were seated at a private computer workstation, where they again completed the physical symptoms inventory and the depression inventory. After completing those measures, participants were debriefed and thanked.

RESULTS

RELATIONSHIPS AMONG SELF–COMPLEXITY MEASURES

Descriptive statistics and intercorrelations for the AST self–complexity measures, stress, and outcomes are presented in Table 2. First, it is interesting to note that the number of self–aspects generated was highly related to H and, to a lesser degree, the distance–based measure of self–complexity. Indeed, the difference between these two correlations was significant, $t(108)=5.36$, $p<.001$. Thus, both AST self–complexity measures were related to the number of self–aspects (to be expected given the definition of self–complexity) and to each other (also to be expected because

TABLE 2. Descriptives and Intercorrelations for AST Measures, Stress, and Outcomes

	Descriptives		Time 1 Measure Correlations					
	M	*SD*	Number	*H*	Dist.–based	Stress	Symptoms	BDI
Time 1 Measures								
Number of self aspects	4.40	1.96	—					
H–based AST SC	2.45	0.87	.85**	—				
Distance–based AST SC[a]	4.32	7.21	.52**	.29*	—			
Stress	2.94	3.18	.11	.17	.03	—		
Physical Symptoms	23.16	15.72	.09	.06	–.07	.17	—	
Depression	4.53	4.09	.14	.12	–.07	.31**	.53**	—
Time 2 Outcomes								
Physical Symptoms	24.83	19.31	.09	.08	–.18	.24*	.57**	.36**
Depression	4.56	6.04	.19	.17	–.09	.41**	.50**	.72**

Note. $N = 110$; [a]Dimension–based, Euclidean measure of distance–based AST self–complexity. $*p < .05$, $**p < .01$

they should assess a similar construct), but *H* was far more redundant with the number of selves generated than was the distance–based measure, suggesting that the latter may better capture meaningful variability above and beyond the number of self–aspects produced (see Locke, 2003; Rafaeli–Mor & Steinberg, 2002).

TESTING THE BUFFERING HYPOTHESIS

The primary prediction in the current study was a stress by AST self–complexity interaction in predicting changes in well–being over the two–week period. In particular, we were interested in the ability of the AST distance–based index to reveal a pattern consistent with the buffering hypothesis. We also explored whether the more simplistic AST *H*–based index would provide evidence of the buffering effect (Linville, 1987; cf., Rafaeli–Mor & Steinberg, 2002).[4]

To test the buffering hypothesis, a series of multiple regressions were conducted where each Time 2 outcome measure (i.e., physical symptoms, depression) was regressed on its Time 1 measure (to control for baseline well–being), stress (negative events in the past two weeks), AST self–complexity (either *H* or the distance–based index), and the interaction between stress and self–complexity.[5] The buffering hypothesis predicts that the interaction term will make a unique contribution in each regression equation. In particular, it predicts a significant negative interaction term for measures of poorer well–being (i.e., physical symptoms and depression).

As Table 3 shows, in all four regression equations (i.e., two well–being measures × two indexes of AST self–complexity) the Time 1 measure was significantly and positively related to the

4. When considering number of self–aspects generated as an index of self–complexity, no evidence of buffering was found on any of the outcome measures.

5. The predictors were centered in all regression analyses reported in the current work in order to ensure the interaction term was uncorrelated with its constituent effects and to simplify the interpretation (Cohen, Cohen, West, & Aiken, 2003). Further, analysis of variance inflation factors indicated that multicollinearity did not provide any interpretation concerns (see Neter, Kutner, Nachtsheim, & Wasserman, 1996).

TABLE 3. Moderated Regression Analyses Testing the Buffering Hypothesis

Time 2 Outcome	Standardized Regression Weights for Time 1 Predictors			
	Time 1 Measure	Stress	AST SC	Stress × AST SC
Analyses with H AST SC Index				
Physical Symptoms	.55**	.09	.02	.08
Depression	.65**	.22**	.06	–.03
Analyses with distance–based AST SC Index				
Physical Symptoms	.55**	.23**	–.19*	–.18*
Depression	.65**	.29**	–.09	–.16*

Note. $N = 110$; Stress = Time 1 negative two–week life events. $*p < .05$, $**p < .01$

Time 2 outcome, indicating its effectiveness in covarying out baseline levels of well–being. In three of the analyses (*H* AST SC predicting depression, and distance–based AST SC predicting physical symptoms and depression), stress exhibited a unique positive relation, indicating increases in physical symptoms and depression as stress increased. Also, greater AST self–complexity as measured with the distance–based index was related to fewer physical symptoms. Finally, regarding the buffering hypothesis, Table 3 shows no significant stress *x* self–complexity interactions for either analysis using the *H*–based AST index, but significant stress *x* self–complexity interactions for both analyses using the distance–based AST index. The negative beta weights on these two interaction terms were consistent with the buffering hypothesis prediction: physical symptoms and depression decreased as stress and distance–based AST self–complexity increased (see Figure 3). In other words, for those under relatively high stress, greater self–complexity as measured by distance in AST space led to fewer physical symptoms and less depression. Thus, support for the buffering hypothesis was found for physical illness and depression, but only when using the distance–based index of AST self–complexity.

To further assess the unique predictive utility of the distanced–based (vs. *H*) index of AST self–complexity for revealing

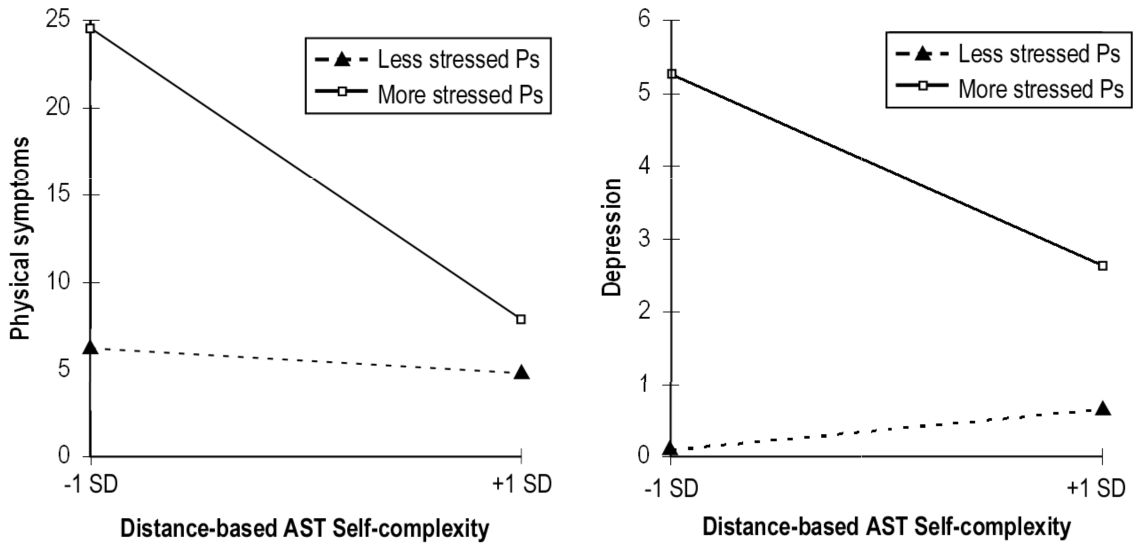

FIGURE 3. Interaction regression plots showing the relation between distanced-based AST self-complexity (x-axis, ranging ±1*SD* from mean) for those relatively greater or lower in stress (separate lines, ±1*SD* from mean) for physical symptoms (top panel) and depression (bottom panel).

the buffering effect, additional multiple regression analyses were conducted, where each Time 2 outcome was regressed on its Time 1 counterpart, the distance–based index, *H*, stress, and the buffering–relevant two–way interactions (i.e., *H x* stress, distanced–based index *x* stress). The distance–based index by stress interaction continued to uniquely predict both physical symptoms ($\beta=-.33$, $p<.01$) and depression ($\beta=-.18$, $p<.05$), whereas there was no evidence of the *H* by stress interaction.

DISCUSSION

The current study explored the buffering hypothesis using a new approach to measuring self–complexity derived from AST, and the results indicated that it fared reasonably well. First, the distance–based AST self–complexity index showed correspondence both to the number of self–aspects generated and to *H*, indicating that it was related to constructs commonly associated with self–complexity. More important, stress by AST self–complexity interactions were observed for depression and for physical illnesses when using the distance–based index of self–complexity, and the form of these interactions replicated the buffering effect. However, buffering was only observed for this distance–based index and not for the more simplistic approach using *H*. In addition, the distance–based index uniquely revealed the buffering effect even when evaluating it and *H* simultaneously. These findings support our contention that the index assessing the *relatedness* of self–aspects and attributes, as opposed to merely their *redundancy*, better captures the processes underlying the buffering effect.

IMPLICATIONS FOR SELF–COMPLEXITY

The current work provides support for the predictions of the buffering model of self–complexity (Linville, 1987) and suggests that buffering can be achieved with a different approach to measurement (an important test for any model or theory)—in particular, one that includes a wider variety of attributes associated with the self and is more sensitive to relatedness among these attributes.

We would argue that an AST–based approach to self–complexity offers many advantages over more traditional methods. First, it provides a conceptualization of self–representation that includes not only traits, but also one's physical characteristics, social categories, relationships to others, and emotional states, among others. Thus, it captures the greater richness of the self that trait–based measures of self–complexity cannot. Beyond the stimulus materials, AST also offers a very different approach to scoring self–complexity. Rather than assessing redundancy in trait usage, AST provides a means by which relatedness among self–relevant attributes can be considered and measured (i.e., their location in AST space). Finally, and perhaps most important, our distance–based index of AST self–complexity is based on assumptions about how social information is represented and activated in memory (e.g., more proximal representations are more likely to be associated and coactivated in memory). For all of these reasons, our AST–based approach offers several sizable advantages over more traditional approaches to self–complexity.

However, there are some caveats regarding these advantages. First, we only observed buffering with AST–based stimulus materials when scoring self–complexity based on the process components of the theory (i.e., isolation of aspects in AST space). In other words, the arguable superiority (in terms of revealing buffering) of the current AST approach to measuring self–complexity likely does not lie in the stimulus materials alone; rather, it appears that the varied nature of the AST self–descriptors only works in conjunction with a scoring method that considers their distance in AST space. Somewhat related, it might be argued that part of the inability to observe buffering in the current study for the more simplistic *H* measure hinges, in part, on using a range of attributes that go beyond personality traits (and thus they are much better suited for an AST distance–based measure than *H*). However, because *H* is insensitive to qualitative differences among attributes (i.e., their content), it is not clear why the nature of the attributes alone would result in *H* failing to reveal the buffering effect. Finally, future research should directly pit this approach to self–complexity against the more traditional approach (i.e., trait sort and Scott's *H*)—something the current study does not do—by incorporating a within–subjects design and testing for incremental variance in one over the other.

IMPLICATIONS FOR AST

In addition to shedding light on our understanding of self–complexity, the current work also provided a substantial test of AST. For example, we considered the AST proposition that spatially proximal representations are more likely to be associated in memory, and we used this assumption in developing a process through which spillover effects occur. Although we did not test this assumption directly (e.g., obtaining measures of attribute accessibility), we did assess the consequences that more spatially–proximal representations have for well–being, and the findings suggest that the theoretical underpinnings of AST have considerable merit. Clearly, future research should more thoroughly, and more systematically, test the underlying mechanisms assumed to operate in AST. At the very least, the current work suggests that AST may have many fruitful implications for diverse areas of social psychology.

One such area ripe for the application of AST is self–concept representation. Interestingly, all previous tests of AST (i.e., Claypool & Carlston, 2002; Schleicher & Day, 1998) have focused on impressions of others rather than on how self–relevant knowledge is represented. Indeed, applying AST to self–knowledge required some modification to the existing framework (i.e., changing target–referent vs. self–referent to public–self vs. private–self). But despite this adaptation, the AST framework proved useful in capturing important aspects of self–concept representation, which in turn had important implications for well–being. Indeed, the current AST approach is consistent with the growing recognition of the importance of understanding how information about the self is cognitively represented and processed (e.g., Greenwald & Banaji, 1989; Baumeister, 1998; Brown, 1998; Carver, 2001; Kihlstrom & Klein, 1994; Linville & Carlston, 1994; McConnell & Rydell, 2004; McConnell, Rydell, & Leibold, 2002; Showers, Abramson, & Hogan, 1998). Many researchers (e.g., Kendall, 1992) have lamented our poor understanding of structural aspects of healthy and maladaptive thinking and the paucity of tools for measuring the self's cognitive structure. The current findings suggest the potential usefulness of AST, both in terms of its theoretical insights and its approach to measurement.

As discussed above, the AST–based approach captures many important self–relevant features beyond traits. Although the importance of assessing more than just traits has always been acknowledged (e.g., Linville, 1985), research in this area has seemingly forgotten this important point and has instead focused on a self composed solely of traits (e.g., Donahue, Robins, Roberts, & John, 1993; Linville, 1987). In addition to capturing the diversity of people's self–concepts, avoiding a "self–as–traits mentality" will be especially important when studying the self in different settings, such as in interdependent cultures that are less inclined to see the self as made up of stable traits (e.g., Markus & Kitayama, 1991).

Finally, there are several additional "complexities" that future research might undertake. First, the current process–based AST measure of self–complexity was computed based on the theory's tenet that in general and on average, proximal representations are more strongly associated than distant representations. However, as Carlston (1994) notes, there are probably individual exceptions to this general rule, wherein distant forms of representation become closely linked through thought and use. Developing methods to assess these individual differences in associations might increase the predictive value of an AST–based self–complexity measure. Second, future research should focus on antecedents and additional consequences of self–complexity. There is very little work on what factors lead to different levels of self–complexity, and regarding outcomes, there has also been little work aimed at clarifying and elaborating the relation between self–complexity and both affect and behavior. We would submit that AST, with its emphasis on the interplay between experiences and impressions and its incorporation of affect and behavior, can provide advances in both regards.

In sum, the current study provided encouraging support for this fledgling AST–based approach to measuring self–complexity and an important demonstration for the value of process and representation in understanding the self–concept. Future work can hopefully build on this foundation, providing a fuller (i.e., more complex) account of how the self is represented in memory and how its representation has meaningful implications for well–being and social functioning in everyday life.

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