Computer Based Measures of Referential Activity and their Use as Measures of Episodic Memory

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abstract

This paper describes the Discourse Attributes Analysis Program (DAAP) and uses it to compare two approaches to operationalizing the construct of episodic memory: a measure that is in current use based on counts of details concerning a specific personal event; and a measure of Referential Activity, characterized as the connection of bodily, sensory and emotional information to language, that has not previously been applied for this purpose. Episodic memory is characterized as personal memory of a specific event of one's life, contrasting with semantic memory, which involves general knowledge. Computer scored measures of referential activity showed large correlations with judge-scored measures based on counts of details on a data set provided by Addis, Wong & Schacter (2008) . DAAP also produces a visually smooth density function that shows moment-by-moment correspondence of the two measures within each narrative. Similarities and differences between the measures and their conceptual implications are discussed.

The concept of *Referential Activity* (RA) was initially developed in the framework of Paivio's (1990) dual code theory that involved systems of imagery and language joined by referential connections and was then expanded to a multiple code theory by Bucci (1997). Referential activity (RA) is defined as activity of the system of connections between language, which consists of discrete symbolic forms, and subsymbolic information, which includes continuously changing sensory, bodily, affective and imagistic experience (Bucci, 1997). According to the theory underlying RA, detailed descriptions of images and events constitute a primary means by which subsymbolic experience can be connected to language. When a speaker experiences an event in the moment of telling it, she activates associated bodily and sensory experience (in at least trace form). According to the theory, the language she uses in connection with these experiences will tend to be more concrete, specific, clear and imagistic. (Bucci, 1997, 2011). A computer program, the Discourse Attributes Analysis Program (DAAP) and dictionaries, including the Weighted Referential Activity Dictionary (WRAD) have been developed to measure the extent to which a speaker or writer is currently engaged in this and related experiences.

In this paper, we describe the Discourse Attributes Analysis Program (DAAP) along with its major features and utilize this system to compare referential activity (measured as WRAD) to episodic memory strength (measured as the proportion of details pertaining to a central event). Through this comparison we will show that these constructs are empirically as well as conceptually related.

The concept of referential activity bears a strong conceptual relationship to episodic memory (EM), which has been defined as memory for personal events that are set in a specific time and place and experienced with contextual details, in a particular state of consciousness involving awareness of the self as a continuous entity across time (Tulving, 2002; Gardiner, 2002). In Tulving's terms, episodic memory "makes possible mental time travel through subjective time, from the present to the past, thus allowing one to re-experience, through autonoetic awareness, one's own previous experiences" (pg. 5). The term "autonoetic awareness" refers to the idea that episodic memory is a mental re-enactment of the time of the event rather than a mere recollection. EM is distinguished from semantic memory, which involves general knowledge about the world and oneself. One might know as facts in semantic memory that the Centre Pompidou is a museum in Paris and that one has visited the museum several times. As an episodic memory, one might relive one's first sight of the Centre Pompidou walking to it on a rainy spring afternoon from the Metro station through the streets near Les Halles.

According to Bucci's theory (1997), when telling about one's first sight of the Centre Pompdiou, the smell of the rain, the dampness of the air, the sounds and lights of the Metro station and the full array of subsymbolic sensory and somatic experiences associated with the event would be activated. When the speaker describes this event, with reference to these experiences, his language would be expected to be high in referential activity (RA).

Measures of RA, including computer assisted procedures, have been developed and applied in a wide range of studies, but have not previously been used to assess episodic memory. In this study, computer generated measures of Referential Activity will be compared to measures of episodic memory based on counts of details as rated by judges. Both procedures will be applied to a set of interviews collected by Addis, Wong and Schacter (2008)[1] and rated by them for episodic memory using a version of the approach developed by Levine Svoboda, Hay, Winocur and Moscovitch (2002). The measures will be compared in terms of overall relationships and point-by-point comparisons within narratives, using the capabilities of the Discourse Attributes Analysis Program (DAAP). We expect that the two measures will show strong relationships as well as some differences.

Overall Review of Methods

Measurement of episodic memory based on contextual details

In several recent studies, episodic memory has been assessed using counts of contextual details pertaining to specific personal events as described by participants (Levine et al., 2002). Their method is based on counts of details as reported in narratives of specific personal events drawn from autobiographical memory. They distinguished *Internal* details relating directly to a central event and specific to time and place from *External* details, including semantic information, such as general factual information, as well as extended events that did not require recollection of a specific time and place, repetitions, and details pertaining to specific autobiographical events other than the main defined event. A ratio of internal-to-total details was computed for each memory as an indicator of episodic re-experiencing unbiased by total verbal output. An adapted version of this method was applied by Addis, et al. (2008) to assess verbal expression of episodic memory in the data set used in this study, including narratives of future as well as past events. Details of the adapted method as applied to the data of this study will be described in the Procedures section below.

Referential Activity and its Measurement

[1] We thank Daniel Schacter for providing us with these texts, scored for internal and external details.

As mentioned above, the concept of Referential Activity was initially developed in the framework of Paivio's (1990) dual code theory that involved systems of imagery and language joined by referential connections. Bucci (1997) then expanded the model to a multiple code theory including subsymbolic information in continuous format as well as symbolic forms. Within this context, Referential Activity (RA) is defined as activity of the system of connections between nonverbal processes - including all manner of bodily, sensory and affective experience - and language. The connecting process is inherently partial and indirect; experience in subsymbolic continuous format cannot be connected directly to the discrete forms of words. The connections are made by describing images and events that are closely associated with underlying networks of subsymbolic experience in the speaker or writer and serve to evoke corresponding experience in a listener or reader (Bucci, 1997, 2011).

The original measure of RA (Bucci & McKay, 2002) consisted of four scales rated by judges: *Concreteness*, referring to bodily and sensory contents; *Specificity*, involving reference to particular people, objects and events, placed in space and time; *Clarity*, referring primarily to understandability of language, including indications of transitions and awareness of the listener's perspective; and *Imagery* as evoked in a listener or reader. The scales may be applied to transcripts of spoken language or to written language. Judges rate texts or segments of text on each scale, ranging from 0 to 10; an overall RA score is computed as the average of the four scale scores. Judges are trained until they achieve relatively high reliability (intraclass correlations among raters of at least .80).

A first generation computerized RA measure (the CRA) was constructed by Mergenthaler & Bucci (1999) by modeling the RA average scale scores. The current computerized measure of RA is the Weighted Referential Activity Dictionary (WRAD) of Bucci & Maskit (2006), also constructed by empirically modeling judges' RA scale scores using a different modeling procedure that produces a weighted dictionary. A large set of texts was scored by judges for the four referential activity (RA) scales and an overall RA score for each text was computed as the average of the four scales. The occurrences of all items with frequency of at least 1 in 1000 words in the text corpus were divided into six categories based on RA scale levels. Each item in the WRAD was then weighted according to its distribution of occurrences within these categories. (See Bucci & Maskit, 2006 for a detailed description of the construction of the WRAD, including weighting procedures.)

The WRAD contains approximately 700 items, primarily function words such as articles and conjunctions, and also includes parts of contractions (such as ‘t’, as in ‘don’t’), several disambiguated common words, such as forms of 'like', and a generic symbol, 'mm', for non-speech sounds usually transcribed as 'uhm' or 'um'. The 20 most frequent items in the WRAD, with their weights, are listed in Table 1.

Insert Table 1 about here

In general, WRAD covers about 80 - 85% of spoken language; the coverage varied between 83 and 87% in the samples used to make and test the WRAD (Bucci & Maskit, 2006); the coverage by WRAD of the texts used here is 79%. The high coverage is due in large part to the dominance of very high frequency function words. The coverage for written language tends to be somewhat lower, due in part to the absence of lexical items such as ‘mm’, marking filled pauses, and other disfluencies that have high frequency in spoken language. Words that are used much more frequently in high RA language, such as *and, the, in, she* and *were* have high weights; words, such as *I, of* and *is*, which are used more frequently in low RA language, have low weights.[2]

We note that the five most frequent words in the data set provided by Addis et al. (2008) are exactly the same five most frequent words, in the same order, in the data set used to construct the WRAD; these five words, *I, and, the, to, it*, alone account for 17.7% of the total word count in the sample used to make and test the WRAD, and 19.3% of the Addis et al. (2008) data. Similar results regarding comparative frequencies and proportions have been found for a wide range of samples, including the spoken language of children as young as 3-4 years old (Shaw, 2014). The full WRAD list of words with their weights, in alphabetical order, can be downloaded from https://github.com/DAAP or www.thereferentialprocess.org/the-discourse-attributes-analysis-program-daap.

Unlike most computer measures in current use, the WRAD serves as a measure of language style rather than particular content areas, and can be applied across a wide range of written and spoken (transcribed) types of material. As shown in Table 1, items with highest weights (dominant in high WRAD speech) are words that point to specific entities (*the* and *a*), join entities (*and*), and designate specific individuals (the third person singular pronouns *he* and *she*), as well as spatial prepositions (*in* and *on*), and past tense indicators (*was*); these are the kind of words people use without intentional choice to tell stories and describe images (Bucci & Maskit, 2007).

[2] The dictionary weights reported in Bucci & Maskit (2006) lie between -1 and +1. The DAAP program assigns the weight 0 to all words not in the dictionary, and then linearly transforms the weights so that they lie between 0 and 1, as shown in Table 1; the neutral value of .5 is assigned to words not in the dictionary.

Supporting this claim, RA measured by WRAD has been shown to have a strong correlation (r_s= .69) with an independent measure of narrativity based on temporal sequencing in a study of responses of 55 adolescents who were asked to tell the story of "your most stressful life event" (Nelson, Moscovitz & Steiner, 2008). Also as predicted, based on the theory that high RA language reflects connections to networks of inner experience, moderate to strong correlations were found between the mean WRAD score and clinical judgments of session effectiveness in a study of recorded therapy sessions (Bucci & Maskit, 2007).

WRAD currently exists in English (Bucci & Maskit, 2006), Italian (Mariani, Maskit, Bucci & DeCoro, 2013) and Spanish (Roussos & O'Connell, 2005). Mariani et al. studied three successful psychotherapy treatments using the Italian version of WRAD (I-WRAD); as predicted, for the patient's speech, levels of I-WRAD increased significantly over the course of treatment.

The Discourse Attributes Analysis Program (DAAP)

Like most current quantitative text analysis systems, the Discourse Attributes Analysis Program (DAAP)[3] uses word lists called dictionaries, including the weighted RA dictionary (WRAD), to compute attributes of a given text. DAAP permits but does not require user-defined segmentation; the several different segmentations used in the current study are described below. Each word of each segment of text is matched against each dictionary. For an unweighted dictionary, the weight at a word is 1 if the word matches the dictionary; it is 0 otherwise.

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[3] The current DAAP software, DAAP09.6, instructions for its use and dictionaries for English transcripts are publicly available at https://github.com/DAAP or www.thereferentialprocess.org/the-discourse-attributes-analysis-program-daap. A description of the workings and mathematical underpinnings of DAAP can be found in Maskit (2014).

Special Features of DAAP

Density functions. For each dictionary and each segment, DAAP uses the dictionary weights of the words in the segment to compute density functions. The density function is defined at each word of the segment of text, based on a moving weighted average of the dictionary weights. Dictionary weights, as transformed by DAAP, all lie between 0 and 1; the values of this density function likewise lie between 0 and 1. As described below, DAAP also constructs density functions based on groups of words as determined by user-defined segmentation; that is, each word in a segment of text is given the same weight, depending on the segmentation marking. The significance of these density functions lies in our basic assumption that each density function, as defined by a dictionary or by segmentation, provides an indicator of some underlying psychological or linguistic variable. Using these density functions, DAAP produces statistics for each segment, each associated group of segments and each text. These statistics include the following, which are used in the current study and will be described below: mean of the density function (which is equal to the mean of the dictionary weights), the High WRAD Proportion, and covariations between pairs of density functions. As will be demonstrated, for segments between approximately 100 and 10,000 words, the graph or chart of a density function appears as a visually smooth curve that tracks the rise and fall of the underlying variable.

For dictionaries, such as the WRAD, the density function at each word is computed by using a weighted average of the dictionary weights of the word itself and the weights of the closest 99 words in each direction, where the weighting is given by an exponential function closely related to the normal curve. A special adjustment is made at the first and last 99 words of each segment. A major effect of this adjustment is that for each segment the mean of the density function is equal to the mean of the dictionary weights.

DAAP also computes a density function based on user-defined segmentation, where words in the same segment are given the same weight. The density function at a given word is, as above, based on the moving weighted average of these weights; the adjustment near the beginning and end of each segment has the same effect of making the mean of the density function equal to the mean of the weights.

DAAP computes several measures derived from the density function. These are computed for each segment of text, and, using the DAAP aggregation facility, they are computed for each associated aggregate of segments, and also for whole texts.

The High WRAD Proportion (HWP). This is the proportion of words in a segment for which the WRAD density function lies above the WRAD neutral value of .5; it is independent of the amounts by which this density function is above this neutral value.[4] HWP is meant as a measure of the proportion of discourse for which the speaker is engaged in verbally connecting to subsymbolic experience.

Covariations. For each pair of density functions, DAAP computes the covariation of these density functions for each segment (and also for each aggregate of segments, and for the entire text). The covariation is a cosine measure that is mathematically identical to the (Pearson) correlation coefficient[5]. Statistically, however, the two concepts differ in that the Pearson correlation coefficient requires that the data points for each variable be

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[4] DAAP also produces another measure, not used in this study, the Mean High WRAD, which is meant as a measure of the average strength of this connection, averaged over the words for which the WRAD density function is above its neutral value.

[5] The covariation reported in Bucci & Maskit (2007) uses a slightly different mathematical formula.

statistically independent; for the covariation, the values of the density functions at nearby words are based on the weighted averages of the dictionary weights (or weights given by segmentation) at nearby words, and so do not represent statistically independent events

The covariation is interpreted as a measure of the extent to which the underlying psychological variables covary; that is, the extent to which they are simultaneously high and simultaneously low. One cannot assign a probability to any individual covariation, but, as will be demonstrated below, one can statistically compare aggregates of covariations for different segments of the same or different texts. We also describe below some psychological implications of the covariation of the particular density functions we use for this study.

Methods of the Current Study

Materials

The narrative reports used in this study were collected by Addis et al. (2008) for the study of age-related changes in episodic memory, including simulation of future events. The data set contains the transcriptions of 32 participant interviews: 16 younger participants (mean age 25.31, 6 males and 10 females) and 16 older (mean age 72.30, 10 male and 6 females). In the adapted version of the Levine et al. (2002) method used by Addis et al., each participant was given 16 different neutral prompts, such as "shoes" or "photograph", and asked to describe four events in each of four conditions: Past few years, or far past (FP), Past few weeks or near past (NP), Next few weeks or near future (NF), Next few years or far future (FF). The participants were permitted 3 minutes for each response. The responses were transcribed and the transcriptions segmented into details. The details were separately judged as to whether they were internal, external, repetitions or null. There were a small number of null segments (less than 1.6%); these are segments of words that were not scored as being internal, external or repetitions, including the response of 'no' when asked if the participant had anything further to say. In this study, the null segments were not included in the count of details; the repetitions were included with the external details.

Procedures

The electronic versions of the transcripts were put into DAAP format with segmentation markers indicating speaker, time period (FP, NP, NF and FF), time direction (past vs. future), relative time (temporally close vs. temporally distant), prompt number (1 to 4 for each time period), and detail classification (Internal, External, Repetition, Null).

These transcripts were run by DAAP using several different aggregations of data, so as to obtain data concerning each participant, time, time direction, and relative time, for all participants, and for younger and older participants separately. For purposes of statistical analysis, we used the proportion of internal details to total details, INTPROP. This is similar to the statistic used by Levine et al. (2002) who allowed response time to vary freely and used the proportion measure to control for variations in response length. Addis et al. (2008) controlled for length of response by restricting the response time to three minutes for each prompt. Since some people speak more than others[6], and the DAAP/WRAD measures (Mean WRAD and High WRAD Proportion) are dependent on the number of words spoken in response to each prompt, the control based on time was not sufficient for our purposes.

[6] For the 32 participants, the total number of words spoken in the entire timed interview varied between 2,348 and 7,054. The number of words used in responses to the 512 individual prompts varied between 14 and 564.

For the purpose of providing point-by-point comparison between the segmentation into details and the WRAD measures, we used the segmentation into details to construct a new density function called INT. This construction allows the computation of the covariation between the judges' scoring of details and the WRAD density function. The INT density function is constructed using the procedure described above, where a word is given the weight 1 if it is a word in an internal detail; and is given the weight 0 otherwise; that is, the word is given the weight 0 if it is part of an external detail, a repetition or a null segment.

Each response to a prompt contains several turns of speech, with the interviewer sometimes asking the participant to provide additional details, or to tell what they remember (or for the future what they imagine) thinking or feeling. Since the turns of speech belonging to the interviewer followed a structured protocol, they were not rated or used for segmentation; DAAP treated each participant's response to each prompt as a single segment and produced a density function for WRAD (and also for INT) for each such segment[7].

Figure 1 is an illustration of the DAAP output for one set of four prompts for far future events from one (younger) participant. The graph of the INT density function is the heavy line, the lighter line is the graph of the WRAD density function. The density construction starts anew at the beginning of each response to a prompt, thus producing three breaks in these curves. This figure shows the graphs of the two density functions for this participant moving together to varying degrees for all four responses to prompts for this time period.

[7] The production of the INT density is a function of DAAP10.1, which will be available at https://github.com/DAAP in the near future.

Insert Figure 1 about here

Here and in Figure 2 below, we can see the power of the DAAP density operator to show the point-by-point relationship between two variables. We expect that the similarities and differences exhibited by these curves result from conceptual similarities and differences in the measures. The similarities and differences between the two measures, WRAD and INT, and the implications of these will be discussed below.

Results

Correlations

For all 32 participants using responses to all 16 prompts, INTPROP has large correlations with both Mean WRAD, $r(30) = .579$, $p < .001$, and even higher with HWP, $r(30) = .677$, $p < .001$. The mean WRAD scores can be obtained by any quantitative text analysis system that uses weighted dictionaries. The higher correlation is obtained with HWP, which is computed as the proportion of words in a text for which the WRAD density function is above its neutral value of .5; this is specifically a DAAP function.

As described above, the design of the Addis, et al. (2008) study involved narratives of two subgroups of participants (16 each younger and older), covering four time periods (Far Past, Near Past, Near Future, Far Future), where the four time periods are divided into two sets in two different ways, past vs. future, and temporally close vs. temporally distant. For purposes of this study, we report correlations for all participants, and for the major subgroups of Past and Future, Young and Old, and Temporally Close and Distant. As shown in Table 2[8], all correlations for HWP with INTPROP are greater than .5 (large effect size). The correlations of Mean WRAD with INTPROP for narratives

[8] Examination of the distributions of these measures for the 32 participants yields no contraindication to the assumption that these measures are normally distributed.

of past events and for older participants are slightly lower (r =.494 and .440 respectively). Results for finer subgroups using all four time periods of narratives will be presented in more detail in a subsequent paper.

Insert Table 2 about here

The INT density was designed to provide a continuous model of the discrete measure INTPROP. The correlation of Mean INT with INTPROP for the set of all 32 participants is .969; the correlations for the same subsets as given in Table 2 range from .962, to .982, indicating that both variables are measuring the same psychological construct. To provide further validation for the usage of INT, we show in Table 3 the correlations of Mean INT (the mean value of the INT density), with both Mean WRAD and HWP for all participants, and for the same subsets as given in Table 2; these correlations are very close to the corresponding correlations of INTPROP with these variables.

Insert Table 3 about here

Covariations

In contrast to correlations, which measure relationships at the level of the entire text, the covariation of density functions permits point-by-point comparison of the variation of measures within segments of texts. The covariations between the INT and WRAD density functions, computed across all responses to all 16 prompts, ranged from a minimum of -.055 to a maximum of .484, with a mean of .218 (SD = .157), as shown in Table 4. Of the 32 covariations, 30 were positive; the probability of this occurring by chance, as given by the binomial distribution is essentially 0; that is, if one assumes that there is equal probability for the covariation being either positive or negative, then the probability of at least 30 of the 32 covariations being positive is less than .0005. Table 4 also shows the minimum, maximum, mean, SD, number positive and associated probability for these covariations aggregated across the same subsets as those shown in Tables 2 and 3.

Insert Table 4 about here

For the 512 individual responses to prompts (32 participants by 16 prompts each), the minimum covariation of INT and WRAD is -.825; the maximum is .896; the Mean is .107; and the SD is .395. Of the 498 covariations, 295 are positive. (As with the correlation coefficient, the covariation is not defined if either variable is constant; INT has constant value 0 for 13 responses and constant value 1 for one response). The probability of at least 295 positive out of 498 occurring by chance is $< .001$.

Application of covariations in examining point-by-point relationships between variables.

In addition to overall summary data, the covariations have special application for examining convergence and divergence within responses to individual prompts. An example showing generally positive covariation between the INT and WRAD densities was shown in Figure 1. The covariations for these four responses are .616, .246, .895 and .071.

An example showing responses with both positive and negative covariation between INT and WRAD is shown below in Figure 2. In this example, the covariation for the first response is quite high (.762); the WRAD and INT density functions rise and fall together. The covariation for the second prompt is essentially zero (-.036). In the response to the third prompt, WRAD remains high while INT dips to zero, resulting in a covariation of -.224. An explanation for this divergence will be suggested in the discussion section.

Discussion

The major empirical results of this study are the high correlations found between judge-scored measures of episodic memory based on numbers of details, and the computer scored measures of RA. The correlation between the measure of proportion of internal details (INTPROP) and HWP, the proportion of words for which the WRAD density lies above the neutral value of .5, for all participants and all prompts was r = .677, accounting for almost half of the variance in these measures.

The strong correlations between INTPROP and HWP held for all major participant subgroups and response categories; these results suggest that the computerized measures may potentially be useful in place of judges' scoring in studies of episodic memory. We also note that correlations were higher for younger than older participants, and higher for narratives concerning future than past.

The very high correlation between the Mean INT density function and INTPROP (greater than .96 for the overall sample as well as all subsets of participant reported in this study) provides validation for our use of these variables as measures of the same underlying psychological construct. This also provides evidence for the general validity of our procedure of building density functions based on segmentation data.

The mean covariation between the INT and WRAD density functions was generally positive, though not as strong as the correlation results. Participants on average used higher WRAD language while describing internal details, but not necessarily at the same points within a narrative response. The covariation data allow us to look beneath correlations of measures to examine the point-by-point relationship between the two measures **within each response;** we can see where they are simultaneously high, and also where they diverge**.** In the example shown in Figure 2, the response to the third prompt concerns the participant's plans to move to an apartment in the city, have a small dog and house train it. Following her description of the training procedures, she talks about how the dog will behave once he is trained, with a description of how he will be able to go outside on a leash, wearing a jeweled collar, and other vivid details. WRAD remain high, INT goes to zero. From the perspective of RA theory, her language indicates that she continues to be immersed in her fantasy of the future, with activation of sensory experiences as expressed in her associations. From the perspective of the details measure of Levine et al. (2002), this description is no longer restricted to a specific time and place and so is classified as consisting of external details.

Conceptual Implications Concerning Episodic Memory

The measures of internal details and the WRAD measures have both been proposed as measures of episodic memory. Both measures are designed to indicate the degree to which a speaker is experiencing an event of one's life in the moment, a sense of actually living it as it is being described, contrasted with the type of generic knowledge of the world and of one's life that has been termed *semantic memory*, but the two measures view this process from different perspectives. The measure of referential activity, based on multiple code theory, emphasizes the activation of networks of subsymbolic sensory and other bodily experience that can be connected to the symbolic forms of language through describing an event that is relived in the telling; the networks may include associations that are relived as well. The view of episodic memory underlying the measure of internal details emphasizes the specificity of a memory, the capacity to represent a specific event of one's life and to locate it in time and place. Our results raise a question as to the degree to which the two views of episodic memory generally converge, and the distinctions between them.

In an important early paper, written from a psychiatric perspective, Andreason et al. (1995) distinguished two kinds of personal memory that they termed *focused episodic memory* and *random episodic memory.* Focused episodic memory involves the type of conscious, directed recall of the events of an individual's past that is called for in taking a psychiatric history. This was contrasted with unfocused retrieval and expression of experience linked in a variety of ways that may not be immediately or manifestly obvious, characterized as free association in a psychoanalytic situation. Andreason et al. characterize this as:

> "…the kind of mental process that occurs when a person eliminates motor and sensory input by stretching out on a bed with eyes closed and 'just thinks'; this mental process, which connects apparently unlinked things without conscious effort, is an important resource for creativity. The thinking tapped during free association (in its full breadth of definitions) is a type of episodic memory, in that it is personal, individual, and autonoetic" (p. 1577).

Andreason et al. referred to this state as *random episodic silent thinking* (REST). They note further that: "The acronym is intentionally ironic, indicating that the 'resting brain' is both active and interesting'.

Buckner et al. (2008) have pointed to insights that emerged from the study of Andreason et al. (1995) that foreshadow current research on the structure and function of the brain's default network: in particular, that the state of unfocused free-ranging thinking is active and vigorous, consisting of "a mixture of freely wandering past recollections, future plans, and other personal thoughts and experiences". They also find similarities to the findings of Andreason et al. in their analysis of brain activity during the rest state.

Our study supports the view of episodic memory as a multi-faceted process. We suggest that the referential activity measures emphasize the associative functions that are central to this process and are most closely related to the aspect of episodic memory associated with the REST state, in the terms of Andreason et al. (1995), and also with the default network, as currently being investigated by Buckner et al. (2008) and many others, while the measure based on internal details may be closer to certain processes involved in focused episodic memory. These differences and their implications, as well as the differences between the autobiographical memories of younger and older participants, concerning narratives of past and future, and narratives concerning temporally close and temporally distant events, will be explored in a forthcoming paper.

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