

Using Computational Linguistics to Understand Near-Death Experiences Concurrent Validity for the NDE Scale¹

Rense Lange
*Division of Research and Development
Integrated Knowledge Systems
Chatham, IL 62629 USA*

Bruce Greyson
*Division of Perceptual Studies
Dept. of Psychiatry & Neurobehavioral Sciences
University of Virginia Health System
Charlottesville, VA 22908-0152 USA*

James Houran
*Division of Research and Development
Integrated Knowledge Systems
Grapevine, TX 76051 USA*

Abstract

Latent semantic analysis – a technique to quantify qualitative data – was used on a large dataset of verbal NDE accounts for which a sizable portion also had scores on Greyson's NDE Scale. Given previous research with the NDE Scale showing there is a core NDE comprised of a probabilistic hierarchy of cognitive, affective, transcendental and paranormal components, we hypothesized that there would be a similar hierarchy of experiential components reflected in NDErs' verbal accounts as evidenced by a significant relation between NDE intensity and NDE content. Predictions were largely confirmed. The verbal accounts associated with True NDEs, defined by median scores on the NDE Scale, stood out as highly structured episodes with a clear framework comprised of seven major linguistic clusters of descriptors. Four of the linguistic factors included transcendent or paranormal themes, whereas the remaining three factors tended to focus on both vague and specific references to physiological or environmental elements. Taken together, the results validate the concurrent validity of the NDE Scale and suggest narratives that reflect a continuity of acute awareness on the part of experiencers that does not make obvious sense in terms of a reductionist model of NDEs whereby sensory faculties are substantially compromised, altered or absent due to a vivid internal attention state, dissociative episode or medical crisis.

Running Head: SEMANTIC ANALYSIS OF NDEs

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Introduction

The medical and social sciences have long known that some adults and children suddenly faced with death experience a distinctive state of consciousness in which their existence was seemingly unbounded by the physical body or earthly environs (e.g., Ring, 1980; Locke & Shontz, 1983; Blackmore, 1996). Termed a *near-death experience* (NDE), this state is defined as a transcendental experience precipitated by a confrontation with death and which does not seem to be adequately understood as the mere phenomenology of a dying or medically-compromised body (for a review, see: Greyson, Kelly, & Kelly, 2009). NDEs are among the most dramatic of exceptional human experiences (Holden, Greyson & James, 2009) with many percipients interpreting them partly or wholly as "mystical, spiritual or paranormal" occurrences. In fact, the *Diagnostic Manual of Statistical and Mental Disorders* added the V-Code category "Religious or Spiritual Problem" in part to acknowledge and guide clinicians in addressing the impact and aftereffects of NDEs and related experiences (Lukoff, 1998; Turner, Lukoff, Barnhouse, & Lu, 1995).

To advance clinical and empirical work in this area psychiatrist Bruce Greyson designed the NDE Scale (Greyson, 1983, 1985, 1990) to quantify the *intensity* of NDEs according to their cognitive, affective, transcendental and paranormal components. The instrument has proved useful in several applications (see e.g., Holden, Greyson, & James, 2009), especially for distinguishing "True NDEs" from other types. In support of its face-validity, the items in this scale were derived from accounts of people (referred to as NDErs) who spontaneously contacted the second author in order to share their experiences when they had come close to death. Lange, Greyson and Houran (2004) published a provocative study in which for those with "True NDEs" Greyson's NDE Scale satisfactorily fit a Rasch (1960/1980) scale model, thus yielding a unidimensional measure with interval-level scaling properties. With increasing intensity, NDEs were found to reflect peace, joy and harmony, followed by insight and mystical or religious experiences, while the most intense NDEs involved an awareness of things occurring in a different place or time. By the very nature of Rasch scaling, components mentioned later in this NDE sequence become salient only after those early in the sequence have already been reported with considerable likelihood (cf. Bond & Fox, 2007) - i.e., NDE components are cumulative.

Further, the semantics of this "NDE core experience" variable were invariant across True-NDErs' sex, current age, age at time of NDE, and latency and intensity of the NDE, thus establishing "True NDEs" as 'core' experiences whose meaning is unaffected by external variables, regardless of variations in the intensity of the NDE. This study was the first to establish in a psychometric sense that NDEs are defined by a hierarchy of experiences that agrees with previous theory and research, while simultaneously pointing the way to new research approaches.

The present research now aims to support the NDE Scale's concurrent validity by providing a direct link between NDErs' verbal accounts, which are available in written form, and the intensity of their experiences as expressed on the NDE Scale. As we explain in the following section, we use Latent Semantic Analysis (LSA) to express verbal accounts in a form suitable for quantitative analysis (see e.g., Deerwester et al., 1990; Landauer, Folz, & Latham, 1998). Once such narratives are represented in quantitative form via LSA, standard statistical techniques can be used to establish concurrent validity. Under the assumption that a similar hierarchy of experiential components is reflected in NDErs' verbal accounts of their experiences, we specifically hypothesize that a significant relation should exist between NDE intensity and NDE content. No exact match between the items and NDErs accounts is required as LSA will recognize terms that are (nearly) synonymous. Operationally, this implies that scores on the NDE Scale associated with a particular NDE account can be predicted from the meaning of their (free-format) written accounts thereof. If so, we will have obtained a system that is capable of understanding at least some aspects of NDEs.

Using the terminology of Schwartz *et al.* (2014), LSA provides an "open-vocabulary" approach that does not require a predefined set of keywords. Rather, given a collection of NDE accounts, relevant words and word sequences are identified using unsupervised learning. While this study research focuses on establishing the concurrent validity of the NDE Scale, it also serves as a general case study of LSA as a new tool for establishing concurrent validity based on the use of qualitative verbal information, as well as an effective method for understanding subjective, narrative-based data from other aspects of psychiatry and social science (see e.g., Osbourne, 1994).

Method

Latent Semantic Analysis. LSA aims to represent passages of text as points in (very high) dimensional space (for an overview, see, e.g., Landauer, Foltz, & Laham, 1998). LSA revolves around the concepts of *corpus*, *tokens*, *vector space*, and *model*. A *corpus* is a collection of text units (e.g., electronic documents, typed answers), called documents. The words in these documents define a series of *tokens* that represent useful aspects of the answers' semantics. Tokens deemed useful in a particular application are gathered in a dictionary, and words not in that dictionary are simply ignored. For instance, the word "the" is probably useless in most contexts and will not appear in the dictionary. The *Vector Space* approach represents documents' tokens as vector features combined with their frequencies. For instance, the sentence "The soldier saw another soldier approaching" might be represented as the token vector [{"soldier",2}, {"approaching",1}, {"saw",1}], while the word "the" is ignored. Word order plays no role here, and the preceding is referred to as the "bag of word" approach.

The Vector Space Model (VSM) assumes that similar documents have similar vectors and that vector similarity reflects similarity in meaning. Experience indicates that first transforming tokens' raw frequencies using a log entropy weighting function supports these assumptions (see, e.g., Manning and Schütze, 1999). In this approach, if tf_{ij} represents the number of times token i occurs in document j , then each token i receives a global weight g_i , defined as:

$$g_i = 1 + (\sum p_{ij} \log_2(p_{ij})) / \log_2 n,$$

where n is the number of documents in the entire corpus, and p_{ij} is the probability of the term i appearing in the document j . The local weight of this term inside a particular document j is then defined as:

$$l_i = \log_2(1 + tf_{ij})g_i$$

The net effect of this approach is to reduce the relative importance of high frequency tokens, while assigning higher weights to tokens that distinguish between different documents.

LSA proceeds to decompose the weighted *document-by-token* data matrix A into the product of three matrices: an orthonormal *document-by- k* matrix T , a $k \times k$ diagonal matrix of singular-values s_{ij} with $s_{ii} \leq s_{(i-1)(i-1)}$, and an orthonormal *document-by- k* matrix D . The value of k represents the number of singular values in truncated versions of T , S , and D that allows A to be reconstructed with acceptable loss of information, while reducing noise and variability (Berry, 1995).

$$A \approx T_k S_k D'_k.$$

Although the optimal number of factors will vary between applications, values of k in the range 100-300 are typical (Landauer, 2007). LSA essentially reduces the size of the document vectors by placing (near) synonyms at similar locations in the k -dimensional vector space.

In this paper we take these reduced vectors as our basic units of observation and as input for further analysis. While LSA works well in practice, even for relatively small samples, the factors it produces are typically difficult to interpret. Other vector-based methods, like Latent Dirichlet Analysis (LDA), tend to be superior in this respect (e.g., Blei, Ng, & Jordan, 2003). However, LDA also requires a larger corpus of cases than is available here.

Data. The second author maintains an ongoing database of NDE accounts often provided personally by those reporting NDEs. Available for analysis were a total of 863 such accounts, some of which constitute only a couple of paragraphs, whereas others span 10-20 typewritten pages. On average, the accounts contain 224.90 tokens ($SD = 146.98$).

NDE Scale. For 553 accounts also were available participants' overall scores on Greyson's (1983, 1985, 1990) NDE Scale. This scale is defined by 16 experiential items derived from hundreds of NDE accounts, and it correlates highly with other NDE measures. Each of the 16 individual components is rated in terms of three ordered categories which generically represent 'not present,' 'mildly or ambiguously present' or 'definitively present', but whose exact wording varies with the nature of questions. Items' response categories are scored 0, 1 and 2, and thus a maximum score of 32 can be achieved. A sum score of 7 or more was chosen as the criterion for identifying someone with NDE. This choice was later validated in a comparison between NDErs and people who had come close to death without an NDE (Greyson, 1990). Three additional groups of respondents can also be distinguished: (1) "Non-NDErs" – those who came near death but denied having had an NDE (with score < 7), (2) "False Positives" -- those who claimed to have had an NDE but score < 7, (3) "False Negatives" – those who denied having had an NDE but score > 7. Using the parameters listed in Lange et al. (2004), maximum likelihood estimates of respondents' Rasch NDE intensity were computed for each respondent ($M = -0.17$, $SD = 1.34$ logits) using the UCON method described in Wright and Masters (1982).

Data Preparation. As recommended by Berry and Browne (2005), the narratives were first “purified” to eliminate tokens providing little useful information. First, to minimize the occurrence of spurious tokens, all accounts were spell-checked using Norvig’s (2007) software, and all proposed changes were verified manually before being accepted. Also, words were normalized to their essential roots by a process known as stemming (Berry & Browne, 2005). For example, and depending on the stemming method being used, the words “fishing,” “fished,” and “fisher” would reduce to the root “fish.” Such stems need not be part of the (natural) language, but stemming assumes that words with a common stem usually have strongly related meanings. For instance, the words “argue,” “argued,” and “argues” reduced to the stem “argu.” All stemming operations are based on the widely used Porter algorithm, as is included in the Gensim (Řehůřek & Sojka, 2010) software,

The resulting tokens were all written in lower case letters, with end-of-sentence markers (i.e., “!”, “?”, or “.”) denoted by ‘#’. Some concepts are defined by a sequence of two words rather than a single word (e.g., New York, well-defined). To capture such cases, all possible pairs of adjacent elements in a sentence, or *bigrams*, were added as well. The present corpus was deemed too small to also use sequences of more than two words. Finally, tokens that either occurred very frequently (in more than 2/3 of all accounts) as well as tokens occurring very infrequently (in fewer than 5 cases) were omitted as these provide very little or very unreliable information. This last condition removed all but the most frequently occurring bigrams.

SVD Software. All LSA analyses reported here are based on Řehůřek’s and Sojka (2010) versatile Gensim system that can be downloaded from [http:// http://radimrehurek.com/gensim/install.html](http://http://radimrehurek.com/gensim/install.html). This Python based software contains libraries for topic modeling, document indexing and similarity retrieval for large corpora of texts.

Insert Table 1 about here

Results

A file was created with the 588 respondents' scores on Greyson's (1983) NDE Scale (when available), together with the coordinates of their accounts projected in a 400 dimensional space (see Method section). These dimensions were ordered according to their corresponding eigenvalues. Using the *glm* procedure provided by the R language, the first 50, 100, ..., 400 coordinates were used to predict respondents' Rasch scaled NDE measures in Logits. The second and third columns of Table 1 show the squared multiple correlations for sets of coordinates of varying sizes, as well as the adjusted R^2 which takes into account the number of predictor variables and the sample size.

By definition n , using increasingly complex semantic spaces adds predictive power, as is indicated by the fact that R^2 increases continuously when more predictors are added. However, the adjusted R^2 values, which take into account the number of predictors and the sample size, reach a maximum value (i.e., 0.33) for about 250 predictor variables, and this value is perhaps a more appropriate estimate of the quality of prediction. Yet, the finding that at least one-third of the variation in respondents' quantitative Rasch NDE measures can be predicted from their qualitative NDE accounts strongly supports our hypotheses.

Insert Table 2 about here

Factor Interpretations. With 250 predictors in the multiple regression model, only the contributions of the seven factors shown in Table 2 reach statistical significance at $p < 0.001$. This stringent Type I error level was used given the large number of predictors. Table 2's columns list these factors in extraction order, i.e., lower numbered factors explain more of the variance in the semantic space than do those with higher ordinals. Note that the significant factors cover a wide extraction range (i.e., 4 through 247), indicating that some of the "later" factors, i.e., factors that explain less of the variance in the semantic space, nevertheless contribute significantly to prediction. This interpretation is supported by the finding that the correlation between variance explained by the first 250 factors and their weights in the multiple regression equation is essentially zero ($r = -0.06$).

As a guide to the factors' interpretation, each column lists the 20 tokens with the highest absolute loadings among the xxx entries in the dictionary. For simplicity, the exact loadings are not shown. Rather, as the sign of tokens' loadings (i.e., either positive or negative) is arbitrary, only the juxtaposition of the top

vs. bottom parts of each column matters for a factor's interpretation. It can be seen that some of the factors have a reasonably clear interpretation that agrees with the qualitative findings reported in earlier qualitative research. For instance, the 'core NDE' hierarchy described by Lange *et al.* (2004), by its inherent definition, focuses on many of the transcendental and seemingly paranormal components to many NDE accounts. Interesting, four of the seven major linguistic factors (4, 7, 26, 49) included such themes, whereas the remaining three major linguistic factors (38, 235, 247) tended to include both vague and specific references to physiological or environmental elements that would seem to suggest a continuity of acute awareness on the part of experiencers that does not make obvious sense in terms of a reductionist model of NDEs whereby sensory faculties are substantially compromised, altered or absent due to a vivid internal attention state, dissociative episode or medical crisis. Instead, the factors arguably suggest a stream of consciousness in experiencers that remains grounded to physical realities attending the experience yet is simultaneously expanded to include a layer of transcendental and paranormal-like components. The esoteric and dramatic components to NDEs neither fully define nor dominate NDEs. Instead, the transcendental components in the linguistic factors overwhelmingly complement, as oppose to replace, the physiological and environmental components. It might be expected that percipients would report more rigid separations in levels or aspects of their consciousness if they were experiencing discrete episodes related to profound changes in their psychophysiological state. Obviously more in-depth work is needed to explore the notion of an "expanded versus reduced awareness" raised here.

Age and Gender as Predictors. For 369 respondents with corresponding scores on the NDE Scale, both age and gender were known as well. The fourth and fifth columns in Table 1 show the multiple correlations when the preceding analyses are repeated, but with these two variables included. As before, R^2 increases as more factors are included, rising to 0.96 when the first 350 factors, plus sex and age, are used. Note however that the number of predictors almost equals the sample size and hence the adjusted value drops precipitously. The adjusted R^2 again reaches a maximum for 250 factors, plus sex and age. For that case, the explained variance increases by 6% (i.e., 33 vs. 39%). However, due to the smaller sample size, and perhaps selection factors, all other adjusted R^2 values are lower than before. We conclude that sex and age improves prediction, but only in combination with an optimal selection of the number of semantic factors.

Insert Table 3 about here

Predicting Sex and Age. It can conversely be asked whether NDEs sex and age in the sub-sample of 369 complete cases are reflect in the qualitative nature of their verbal NDE accounts. First, using a variety of approaches, including linear regression, logistic regression, and discriminant analysis, no reliable method could be identified to predict NDEs' sex from the semantic factors, regardless of the number of factors being used. For instance, linear and quadratic discriminant analysis both only allowed the correction of 88% of the cases, which hardly improves the baseline value of 87%.

NDEs' age, by contrast, could be predicted with considerable accuracy. Table 3 shows the R^2 obtained from multiple regression together with their adjusted values, across a varying numbers of factors being used. The analyses were repeated with and without using sex as a predictor and the results are shown in columns 4 and 5, and 2 and 3, respectively. By definition R^2 increases with the number of predictors, but unlike the results in Table 1, so does the adjusted R^2 . Settling this issue probably requires larger samples of observations, but if (as in the prediction of NDE intensity) we use the first 250 factors then about a quarter of the age variation can be explained by the semantic factors. We note that including sex as a predictor consistently has only minimal effects on the adjusted R^2 and this variable can thus be ignored.

Predicting "True NDEs". We noted earlier that a raw sum of 7 or higher on the NDE items is used as a criterion for labeling respondents' experiences as a "True NDE" versus other types. Based on this rule, 523 of the 588 (87%) respondents with NDE scale data were classified as True NDEs. This classification was difficult to predict. For instance, logistic regression in the R programming language using the first 250 factors as predictors, did not converge. Also, standard linear regression to predict NDE categorization failed to reach statistical significance ($R^2 = 0.41$, $F(250,282) < 1.0$), and the results are nonsensical when adjusted for the number of variables and sample size ($R^2 = -0.11$).

Finally, the actual and predicted values in the standard regression approach with 250 predictors (and not including sex and age) discussed in the preceding section were categorized as a True NDE or not based on the Rasch estimates corresponding to a raw score of 7. This yielded 89% correct predictions, i.e., only slightly above the baseline of 87%. We conclude therefore that, at least in the present data set, it is

difficult to distinguish the NDE accounts of those with True NDE from other types.

Discussion

The findings strongly support the concurrent validity of Greyson's (1983, 1985, 1990) NDE Scale by confirming our basic hypothesis that the intensity of NDErs' experiences can be predicted from their written subjective accounts using Latent Semantic Analysis. This statement summarizes a complex chain of events that starts from the assumption that co-occurring words share a similar meaning. The complexity of this approach is reduced through Singular Value Decomposition, which assigns to arbitrary collections of words a location in a semantic space. These spatial coordinates were then successfully used as predictor variables for statistical correlation and prediction. It is important to note that our results are open-vocabulary, i.e., they do not require a predefined set of NDE keywords with a known correspondence to NDE intensity or other variables. Rather, except for some basic rules concerning word occurrence, unsupervised learning proved successful in creating a useful semantic space of NDE's cognitive, affective, transcendental and paranormal components. Currently, once computed for a collection of accounts, this space is static as its structure remains fixed even though new accounts become available. However, should this prove useful, the Gensim software (Řehůřek's & Sojka, 2010) can also update the semantic space incrementally as more accounts become available.

Although we have achieved a useful encoding of NDE accounts that predicts NDE intensity and percipient age, it is legitimate to ask what exactly has been learned. First, the semantic space contained factors that summarize some of the basic themes of NDErs phenomenology, including physical and environmental factors, as well as more esoteric and dramatic perceptions of interest to transpersonal and humanistic-oriented psychologies. Thus, our findings validate earlier research on the robustness of a core NDE (for a review, see: Holden et al., 2009; cf. Lange et al., 2004). Secondly, LSA knowledge is declarative rather than procedural, and it is best seen as "semantic" - i.e., the SVD generated space resembles a generalized record of facts and meanings concerning reality. In a different context, Landauer, Foltz and Laham (1998) argued that LSA offers an approximation to human knowledge in a specified cognitive domain and they observe that:

One might consider LSA's maximal knowledge of the world to be analogous to a well-read nun's knowledge of sex, a level of knowledge

often deemed a sufficient basis for advising the young (Landauer, Foltz, & Laham, 1998, p. 5)

Not unlike the clinical impact NDEs can have on percipients' every day attitudes and experiences observed by Lukoff and colleagues ((Lukoff, 1998; Turner, Lukoff, Barnhouse, & Lu, 1995), we showed earlier (Lange et al., 2004) that NDEs have the power to restructure people's cognitions by re-prioritizing the items they deem relevant. This fact is also reflected in our semantic space, since it proved possible to distinguish reliably between individuals with low vs. high scores on Greyson's NDE scale. The cumulative picture being painted is that "True NDEs" appear to have an inherent, predictable structure that arguably challenges reductionist explanations for their phenomenology. Academia merely has NDE reports to analyze rather than the direct, physical experiences themselves. Therefore, new perspectives and research avenues like LSA hold promise for the development of more highly integrated, multidisciplinary research on the NDE question. The authors therefore seek cross-cultural collaborations to advance research in this area using more and varied datasets to properly test the generalizability of these results.

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Table 1: Summary of predictive power by linguistic dimensions.

	Semantics only ^a		Semantics with Sex and Age ^b	
Number of Dimensions	R^2	Adjusted R^2	R^2	Adjusted R^2
1-400	0.81	0.23	— ^c	—
1-350	0.75	0.28	0.96	0.10
1-300	0.70	0.31	0.87	0.29
1-250	0.64	0.33	0.86	0.39
1-200	0.56	0.29	0.68	0.29
1-150	0.49	0.29	0.57	0.26
1-100	0.42	0.29	0.43	0.27
1-50	0.36	0.29	0.37	0.27

^a $N = 588$

^b $N = 369$, sex and age were added as predictors

^c No meaningful solution exists due to number of predictors and sample size

^a Factors are listed in order of decreasing eigenvalue

^b Tokens are listed in order of decreasing loadings (absolute values)

Table 3: Predicting percipient age across the linguistic dimensions.

			with sex	
Number of Semantic Dimensions	R^2	Adjusted R^2	R^2	Adjusted R^2
1-350	0.98	0.51	0.98	0.48
1-325	0.92	0.35	0.93	0.34
1-300	0.86	0.26	0.87	0.26
1-250	0.76	0.25	0.77	0.27
1-200	0.63	0.19	0.64	0.21
1-150	0.56	0.25	0.57	0.27
1-100	0.41	0.18	0.43	0.21
1-50	0.28	0.17	0.32	0.20