Towards an Index of Mental Wellbeing in Language

The relationship between time orientation, self-focus and mood during prolonged bed-rest.

Schmer-Galunder, Sonja
Smart Information Flow Technologies
Minneapolis, U.S.A.
sgalunder@sift.net

Wu, Peggy
Smart Information Flow Technologies
Minneapolis, U.S.A.
pwu@sift.net

Ott, Tammy
Smart Information Flow Technologies
Minneapolis, U.S.A.
tott@sift.net

Miller, Chris
Smart Information Flow Technologies
Minneapolis, U.S.A.
cmiller@sift.net

Abstract*— Monitoring the mental wellbeing and psychosocial states of human operators in safety-critical domains is key to improving crew performance, safety and security. However, acquiring objective data and insights to mental wellbeing and psychosocial states among human operators is difficult and has relied on the subjective reports of operators, which are prone to biases and distortions. Team communications in a broad range of contexts from business organizations to high criticality workplaces such as emergency response, airplane pilots and spaceflight could be significantly improved with quick access to reliable and objective data about the psychosocial health of a team. Data on the psycho-social dimensions of collaborative teams, such as social distance, power dynamics, affect, and a team's comfort working together are typically highly subjective, not readily computationally tractable, and are collected using self-reports such as think-aloud protocols or surveys that can confound the behaviors being studied. By developing a method to collect data using non- or minimally intrusive methods requiring low participant effort coupled with automated data processing, we unshackle researchers from the burdens of hand-coding raw data and enable them to make empirically based discoveries more rapidly. This paper presents a validated, cost-effective and fast alternative to the shortcomings of current assessment methods. We present the results from an automatic text analysis tool applied to large amounts of written text (i.e., journals kept by participants in a bed rest study) in order to identify topics of interest, the emotional valence (positivity or negativity) of topics, as well as changes in these metrics over time. These topics and aspects of the text were identified computationally and automatically. This research was performed on different groups of subjects participating in NASA analog studies, where the primary goal of our investigation was the identification of changes to psychosocial states. Our results show that it is possible to predict mood based on journal entries alone using Latent Semantic Analysis *and that we are able to identify non-conscious variables impacting well-being over time.

Keywords—Latent Semantic Analysis; Sociolinguistics; Wellness; Psychosocial State Detection; Sentiment Analysis; Data Mining;

I. Introduction

Relying on self-reports to make assessments about mental wellbeing and psychological health on a continous basis has many potential pitfalls. This is particularly true in the context of long duration experiments such as longitudinal studies that span weeks or months. Respondent fatigue, where participants' attention and motivation to respond drops, is a well documented problem that affects data quality. Survey data is also subject to a participant's memory, biases, vigilance, and personality (e.g., some participants are simply not inherently very self-aware or reflective). Further, self-reports can affect task performance if they impose additional workload, or if the act of reporting is disruptive to the behavior or environment being studied. For example, in an emergency response scenario. In such scenarios, data is often gathered using human observation, which is also prone to errors and omissions.

In the domain of space exploration, NASA has identified the need to monitor individual behavioral and mental health, which is crucial in ensuring high performance and mission success, especially in its vision for deep space, long duration exploration missions. Of particular importance are the detection of changes in mood and mental wellbeing. These changes can be particularly difficult for crew members to detect themselves as fatigue can impair self-reflection. Lack of sleep has been associated with negative mood such as depression and anxiety, however recent findings show that the relationship between sleep and mood is bi-directional, such that daytime mood impacts sleep quality [1]. Sleep deprivation may increase ruminating, defined as compulsively focusing attention on a source of distress. This tends to be associated with remembering negative events from the past rather than contemplating the future [2], and ruminating is considered a vulnerability factor for depression [3]. In contrast, regularly timed exercise impacts mood stability positively and shortened sleep decreases mood stability [4]. Interestingly, time orientation, whether one focuses on the past or the future, might be a mediating factor. For example, Stolarski et al. [5] has found that vivid recall of past negative events worsens reported wellbeing while recall of past positive events has an energizing effect.

Using Linguistic Inquiry Word Count (LIWC) analysis, researchers have consistently found that writing has beneficial effects on wellbeing. For example, changes in insight and causal words over the course of writing are indicative of better mental health, because these word groups represent understanding and organization of thoughts into a more coherent and cohesive personal narrative (Pennebaker and Francis). Other studies found that persons who use a moderate number of negative emotion words, had fewer doctor than those who uses very few or a lot of negative words.

However, while reflective writing can have therapeutic effects on mental wellbeing, reflection can also turn into rumination. Rumination involves focusing repeatedly and passively on what one is feeling and why one is feeling a certain way. It has been shown to increase feelings of anger and aggression [6] and leads to higher levels of depressive symptoms over time [7]. Typically, depressed people tend to think more negatively about the past and tend to recall negative memories of the past more often.

At the same time, self-focus is associated with negative affect, where rumination is a strong mediator [8]. Interestingly, Mor and Winquiest also found that private self-focus is more strongly associated with depression and generalized anxiety, whereas public self-focus is more strongly associate with social anxiety.

But self-focus can take on different perspectives with different outcomes on personal mood and wellbeing. Kross et al found that memories of the past can be described using a self-distanced or a self-immersed perspective. Typically, when people recall negative emotional events, they take on a more self-immersed perspective; re-experience the past event in the first person, through one's own eyes [9]. However, if people take on a more self-distanced perspective, people reconstruct the event in ways that promote insight and closure, leading to less negative affect [10]. This kind of perspective taking can be detected in writing through the use of personal pronouns, past/present/future tense and affect words. However, because these processes happen often in a non-conscious domain, automatic and objective analysis of language can be useful in identifying an index of mental wellbeing.

With the vast improvements in speed and processing power of modern computers, it is now possible to automatically analyze very large text corpora with sophisticated computational models that reveal hidden, or latent, structures in written language that are associated with psychological and emotional states. These models can then be used to accurately and reliably predict psychological and emotional states from writing. These states may not be detectable through human observation. Developing tools like this will be crucial for monitoring space crews' mental health on long haul missions.

The goal of this work is to demonstrate the feasibility of automatically, unobtrusively and objectively detecting changes in mood that may result from participating in prolonged bedrest. Related factors impacting mood can be disturbed sleep, lack of exercise and cognitive factors. Our hypothesis is that mood is expressed unconsciously in the journal writing of participants, represented through the valence, frequency and co-occurrence of certain words. This work furthers the search for reliable and unobtrusive ways to monitor the psychological health of crews in extreme environments.

In preparation for future Mars missions, methods to augment current practices for evaluating psychological health and factors impacting behavior and performance (i.e., mood, sleep, etc.) need to be explored. It is difficult to overstate the value of an accurate, objective, repeatable, efficient, accepted and non-intrusive means of assessing relevant psychosocial states. An automatic, non-intrusive acquisition and processing capability allows researchers to learn and validate virtually everything else necessary for the psychosocial health and performance of future space missions.

II. METHOD

A. Bedrest Study

This study was carried out at NASA's Flight Analog Research Unit (FARU) Bedrest Facility at the University of Texas Medical Branch (UTMB), see Figure 1. The FARU bedrest facility's primary focus was to study the effects of microgravity on human physiology, for example, the effects of exercises and testosterone treatments on muscle and bone mass loss in space. Participants underwent 14 days of intake protocol and were then confined to bed-rest for 70 days, followed by 14 days of recuperation and post-treatment protocols (for more information see [9]). Some subjects work with trainers and exercise up to 9 times per week while maintaining a head-down position. Participants are selected for age, physiological and psychological characteristics analogous to the astronaut population. Subjects maintained a 6-degree head down angle for all activities during the 70-day bed rest period. They were monitored by a human 24/7 to ensure compliance. There were

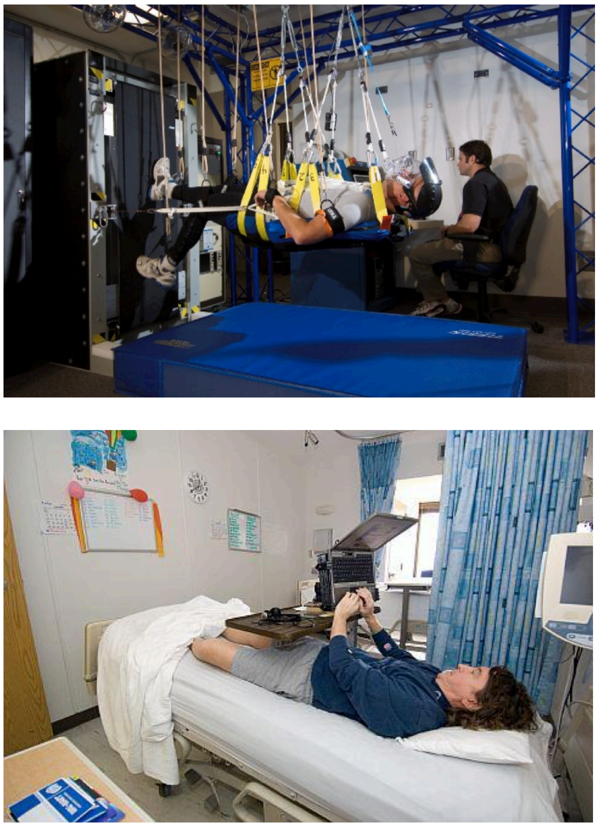


Figure 1. Bedrest Facilities UTMB FARU: (a) Bedrest Subjects on Vertical Treadmill. (b) After an inital 2 weeks of baseline data collection, subjects maintain a 6 degree headdown position for 70 days.

4 different conditions: exercise (E), control (C), exercise & testosterone (EX&T) and freefly (F). Subjects in the exercise condition trained in 9 sessions per week with a human trainer; in the testosterone condition exercisers were additionally injected with a very small amount of testosterone. The control group did not exercise but received a placebo injection. The freeflly condition did mild exercise and no injection/placebo. Physical health, as well as diet, were closely monitored and managed throughout the study. A clinical psychologist evaluated the psychological health of all subjects on a weekly basis.

We collected journal data from 16 bedrest subjects with an average of 83.75 entries per subject. The total word count (WC) of the data corpus is 210,943, with the mean number of words per entry being 174.77. 59,371 (28%) words were provided during 2 weeks of pre-bedrest, with a mean of 242.33 per entry. 132,925 (64%) words were provided during bedrest, with a mean of 165.74 per entry. 18,647 (8%) words were provided during the 2 weeks of post bedrest, with a mean of 116.54 per entry. For this analysis, we included a total of 1174 journal entries.

B. Measures and surveys

Subjects were asked to complete the State Trait Anxiety Inventory (STAI) [11] once as part of intake, and complete the Positive and Negative Affect Schedule (PANAS) once daily. At the end of each day, they complete a 20-minute journal writing session, followed by a short survey asking general questions about their wellbeing, time orientation, self-vs. other focus, depth of thoughts and physical state. After they complete the 70-day bed rest, they are debriefed on their journaling results and general experience. Facility staff completed daily surveys about their general observations of a subject. The instructions for the written journal are as follows: “Reflect on your feelings throughout the day. Write in a quiet space without distractions for roughly 20 minutes. Make sure to write at least a half page of text (at least 250 words), though feel free to write more if you wish. Do not worry about spelling, grammar, or repetition.”

C. Latent Semantic Analysis and Valence calculations

Latent Semantic Analysis (LSA) is a computational algorithm that captures the occurrence and relative position of words and their semantic equivalents, and in our case also the valence of texts of interest. The term “valence” refers to general pleasantness vs. unpleasantness and it refers to a numeric value that we are able to deduce from the general tone of any text of interest, ranging from 0 (low valence) to 9 (high valence). To calculate valence, we used 1) LSA to generate a high-dimensional semantic space from the entire text corpus, resulting in a matrix where the columns correspond to text contexts (paragraphs, clauses or any other unit comprising a number of words), while every individual word is represented by a row. The matrix describes a high-dimensional space, which we reduced to 100 dimensions for computational efficiency. This is also the optimal number of dimensions that captures the semantic relationships in the text. The model depicts word incidences in different contexts. 2) We then used the Affective Norms of English Words (ANEW) [12] as a dependent measure for a multiple linear regression across the 100 dimensions in the semantic space. The result is the best-fitted valence of the words in the ANEW word list. This yields a predicted valence value for each expression of interest (words, sentences, documents), taking its surrounding context into consideration. Figure 2 shows two writing samples and calculated high/low valence points, based on the content.

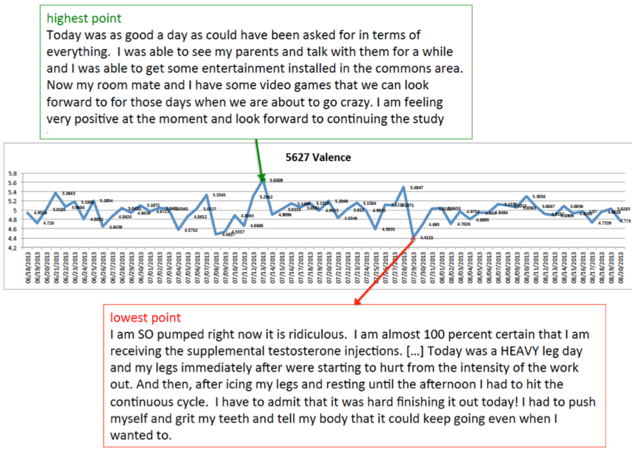


Figure 2. Samples of positive and negative valence of journal entries.

Using this method we calculated valence values for all journal entries and identified high and low points, captured changes over time in mood and we could characterize the contextual circumstances in which a topic is discussed. This essentially provides a method for quantitative analysis of highly qualitative data, enabling, for example, cross-validation of calculated valence with subject survey ratings for affect.

D. Linquisitc Inquiry and Word Count (LIWC)

Linguistic Inquiry and Word Count (LIWC) is a text analysis program based on work by Pennebaker, Booth and Francis [12]. LIWC counts the frequency of an occurrence of a word (or word root) in a given body of text and computes the percentage of total words in defined linguistic categories. The categories include negative emotion words (sad, angry), positive emotion words (happy, laugh), standard function word categories (first, second, and third person pronouns, articles, prepositions), and various content categories (e.g., religion, death, occupation). Words were assigned to specific categories by having groups of judges evaluate the degree to which about 2000 words or word stems were related to each of several dozen categories. LIWC uses the developed "dictionaries" to provide the percent of a given text that can be found in each category.

The computed LIWC score has been shown to correlate with specific attitudes and attributes in the writing of many populations (see [13], [14] for summaries). For example, a category of words associated with cognition and cognitive mechanisms is said to be associated with female speakers/writers, with negative emotions, and with complex reappraisals of situations such as following trauma [13], as well as increased mental health [14].

III. RESULTS

A. Valence predictions of mood over time

Correlational analysis showed that general LSA valence for daily journal entries correlates with daily PANAS survey responses over all bed-rest subjects. Positive Affect (PA) and Negative Affect (NA) scores show significant correlations in the expected direction, where PA correlates positively with valence (r*s*[1174]= 0.159, p<0.001) and NA correlates negatively with valence (r*s*[1174]= -0.105, p<0.001). Thus, using automated tools it is possible to identify general mood without having to ask subjects to fill our surveys.

Moreover, using LSA, it is also possible to pick a random journal entry and *predict* with 63.6 % accuracy the experimental condition (E, C, T or F) of single subjects. The same analysis can be done with survey responses as the predictor variable. This analysis yields an accuracy rate of 59% accuracy for PANAS scores of single journal entries. While the accuracy may seem low, it is important to note that emotional variety of journal entries is relatively high, while PANAS scores represent a single score for affect. Moreover, text-based predictions of PANAS scores can be complimented by the capability to recognize changes such as upward or downward emotional trends, as well as the ability to examine the co-occurring predictions of other factors such as social connectedness, physical wellbeing or sleep. However, using this method, we can reliably predict features like experimental condition or at which day during the 90-day BR a particular journal entry has been written (Figure 3).

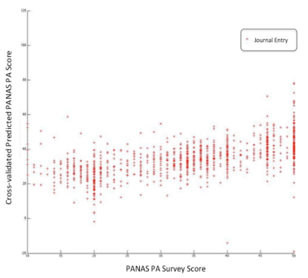
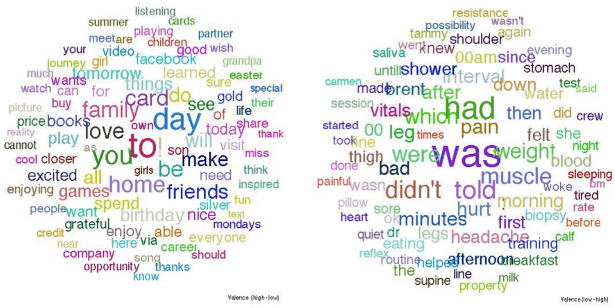


Figure 3. Predicted PANAS score of

B. Positive and Negative topic identification and time orientation in corpora

Apart from simply tracking general mood over time, we investigated larger text corpora (all journal entries of all subjects in the bed-rest study) in order to identify words (topics) with significantly higher (lower) valence in comparison to the rest of the corpus.

Figure 4(a) and 3(b) shows the result of this analysis - visualizations of arising topics in word clouds, where the size of the word indicates higher frequency/importance. During this study most positive topics contexts were “home”, “friends”, “games”, “family”, while words like “muscle”, “pain”, “sleeping”. It is also interesting to note that time orientation in negative contexts is oriented towards the past as represented by the significantly more negative valence of words like “was”, “were”, “told”, “didn’t”, “then” or “done” in comparison to words representative of the present, i.e. “today”, “be”, “play”, “do”, “make” or “here”, which can be found in journal entries having more positive valence. We can also find that focus is more placed on “others” in positive valence contexts (i.e., “you”, “friends”, “family”), are more on the self in negative contexts (in particular own body parts i.e., “stomach”, “leg”, “thigh” or “shoulder”). These topics are derived from the sum of all journal entries and represent most frequent, or salient topics.



4(a). 4b).

Figure 4. Positive and negative valenced word clouds in LSA space. (a) Substraction of low valenced words (word usage in positive contexts). (b) Substraction of high valenced (negative contexts).

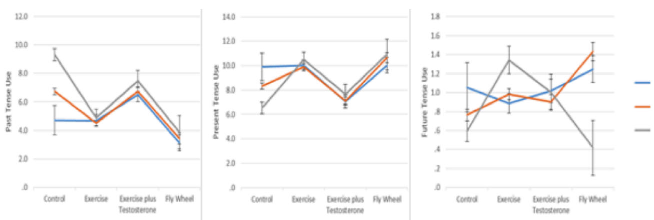


Figure 5. (a) Frequency of past tense by condition (Control, Exercise, Exercise&Testosterone), FlyWheel. (b) Frequency of present tense by condition (c) Frequency of future tense by condition.

C. Self-focus, Time Orientation and Mood

Because our analysis focused preliminary on the relationship between automated analysis of linguistic content and subjective survey responses, we focused on identifying correlations between subjectively reported experience and journal content. What we found in our data is that persons who responded on the self-focus survey being more “other-focused” also reported more Positive Affect (PA) on the PANAS scales, and less Negative Affect (NA), while persons who are more self-focused also feel more negative, and less positive affect. Correlations are significant at p=0.000 for PA with r=0.483 and NA r= -0.395. More self-focus is related to higher LIWC past tense word frequencies, while focus on others is related to less focus on the past. However, we found a negative correlation between past tense words and the word “I” (r=-0.151, p<0.000), and more “I” when writing about the present (r=0.286, p<0.000) and the future (r=0.182, p<0.000), meaning that subjects use less “I” when writing about the past.

One would expect that self-focus as expressed in the use of “I” would yield higher frequencies of “I” in journal entries with a past-focus. However, a more detailed valence analysis revealed that the valence of the word “I” is low in journal entries, which have a focus on the past, while valence of “I” is high when journal entries are more present and future oriented. Further correlational analysis showed that the use of personal pronouns is high when NA is high (r= 0.138, p<0.000) and low when PA is high (r=-0.159, p<0.000). Interestingly, both PA and NA affect responses are low when frequencies of past tense use is high (PA: r= -.263, p<0.000 and NA: r= -.148, p<0.000) while journal entries with a present-focus correlate positively with both PA (r= 0.125, p<0.000) and NA (r=0.221, p<0.000). We found further support for theories that link self-focus with anxiety and negative mood in correlations between time orientation and the STAI. State as well as trait anxiety correlated positively with frequency of past tense use (r= 0.224, p<0.000, r= 0.145, p<0.000), and negatively with future tense use (r = -0.202, p<0.000 for state anxiety, no sig. correlation for state anxiety). As expected, PANAS PA scores correlate negatively with STAI responses (state anxiety: r=-0.226, p<0.000, trait anxiety: r=-0.433, p<0.000) and positively with PANAS NA responses (state anxiety: r= .304, p<0.000, trait anxiety: r=0.196, p<0.000).

In sum, these results confirm current theories that a focus on self correlates negative mood and the recalling of an event in the past, while a focus on others is related to a more positive mood.

D. *Difference between Bedrest Conditions*

Next we looked at differences between conditions. Using a 4 Condition (Control, Exercise, Exercise&Testosterone, Freefly) x 3 Headdown (Head up, Head down, Post-Bedrest) ANOVA analysis, we found a main effect for condition for general valence F(3,1171)=6.697, p=0.000. Controls have lowest overall valence (M=4.95), Exercisers have higher overall valence (M=5.02), followed by the EX&T group (M=5.11) and the freefly group (M=5.09). We also found a main effect for PA F(3,1162)=5.293, p=0.001 and NA F(3,1162)=5.233, p=0.000. Thus, differences between the conditions are significant for both automatically retrieved as well as reported mood. However, there are some interesting differences. While generally speaking, Controls have lowest affect (low valence, high NA and low PA), subjects who exercised have higher reported PA *and* NA as well as higher valence in their journal entries. Subject who exercised, but also received testosterone report both lower PA and NA relative to the exercisers, while their overall valence is highest among all conditions. The freefly condition reports moderate PA, high NA and moderate/high valence. Clearly, there are differences in mood and wellbeing among the different experimental conditions, but in order to understand driving variables, we wanted to understand if self-focus and time orientation play a

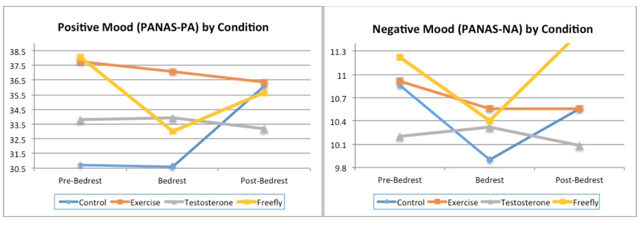


Figure 6. Scores by Group and and Headdown Conditions. (a) Positive Affect (PANAS PA), (b) Negative Affect (PANAS NA).

role. we looked for differences in past, present and future tense usage. We also found an interaction for past tense use, F(6,1172)=2.476, p<.05, present tense use, F(6,1172)=2.275, p<.05, and future tense use, F(6,1172)=3.683, p<.01, see Figure 5. Only the control group differed in past and present tense usage during the different phases of the study. While all groups differed in future tense use. The control group used the most future tense during head-up, the EX group used the most during post bedrest, while the Flywheel used the most during head-down. There was no difference for the EX+T group.

What we found is that Controls report less negative affect and less positive affect when talking about the past, but negative affect when talking about the future. This pattern is reversed for the EX&T condition, which report high PA when talking about the future and very low PA when talking about the past. Maybe the most interesting finding is that the EX&T condition, which has highest overall valence, uses more 3rd person pronouns when talking about the past, but no 3rd person pronouns when talking about the present, but instead more "I". Together with a high correlation of positive affect and present term word usage, this group may have highest overall valence because they are taking on a more self-distanced perspective, as reflected in 3rd person pronoun usage, more positive affect related to the "now" and an absence of negative affect. What is also interesting is that for the Controls, insight and cause words are less used in journal entries focusing on the past in comparison to the other condition, while insight worlds are used by all conditions, but the freefly condition in present-focused journal entries.

IV. CONCLUSIONS

Our results show that automated linguistic analyses on journaling data can provide insights into the mental wellbeing of single persons as well as a number of people of interest. Using LSA derived valence values, we found that is it possible to predict characteristics about journal entries, i.e. time when it was written or experimental condition, by simply looking at the semantic word contexts. Computational methods that are able to predict self-reported survey responses are an attractive alternative to time-consuming survey responses. These methods may also provide the means to send automatic messages back to earth that a team might be in difficulty early enough to take countermeasures. We were also able to identify variables impacting general mood, i.e. time orientation and self/other focus. What we found is that generally, people who are more self-focused also show more negative affect. However, taking on a distanced (vs. immersed) self-perspective, as reflected in the use of 3rd person pronouns as well as insight words, an indicator of better mental wellbeing can be found. For our purposes, PA reflects the activation of positive emotions, feeling enthusiastic, active and alert. High PA is a state of high energy and pleasurable engagement, whereas low PA is characterized by sadness and lethargy. In contrast, NA describes a general dimension of subjective distress and engagement in negative moods such as anger, fear, disgust or nervousness. Low NA is therefore a reflection of not being engaged in negative moods, and may include feeling calm and relaxed. Thus, what we found is that automated textual analysis of valence is able to identify activation of PA and NA. We believe that there are large individual differences in outward expression of emotion either in written or verbal communications, thus correlations may be stronger when averaged over either longer periods of time, or using higher numbers of observations. Longer periods with greater numbers of observations provide individuals with the opportunity to express their emotions through behaviors. This is consistent with our preliminary analysis of verbal communications data,

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which contains much more textual volume per sample, as well as stronger correlations between individual LSA valance components and PANAS.Within the context of long duration missions due to the lack of real-time communication, it is crucial to be able to detect and predict relevant behavioral and mental health metrics of the crew over extended periods of time. In other domains such as healthcare and interpersonal skills training where there is an abundance of narrative data, a process for automatic analysis is sorely needed to reduce the labor costs of manually coding observations.

While the use of journal writing may impose workload on the participant, the writing itself may in fact have positive psychological benefits [15]. In addition to positive and negative affect, the journal text can provide a rich dataset for analyzing multiple factors and sentiment on environmental factors and other contexts. Furthermore, once rich models are developed the system could guide crewmembers in their writing by suggesting the use of, for example, more 3rd person pronouns. This simple change in writing style might improve mood. Unlike surveys, free-form text and communications transcripts may also be mined for constructs that were not conceived a-priori to data collection. Minimally intrusive method of detecting attitudes towards environmental or situational factors and emotional state can help individuals make the connection between precipitating events to changes in moods and attitudes. For example, studies have shown that for 'healthy' persons, narratives of highly stressful events change over the course of time, including expect of their environment and new experience. But there is little change over time to the linguistic content of the narrative of less resilient persons [16]. Moreover, this method can be used for self-monitoring and can help increase individual self-awareness. It can also inform the author about how a message might be perceived by others before the message is sent. Thus, our results are able to provide an objective solution to identifying psycho-social dimensions wellbeing completely unobtrusively.

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