Vivid Memory of “When” a Happy Event Happened is Associated with Mental Well-being: A Natural Language Processing Based Study

Abstract

Background: Overgenerality or specificity of autobiographical memory is associated with psychological disorders such as major depressive disorder, post-traumatic stress disorder, and drug addiction. Current methods to measure overgenerality rely upon researchers’ subjective judgment, although automatic tools can measure other language-based scores for psychological disorder screening.

Objective: This study was conducted to detect time-specific expressions, an aspect of specificity, in an episode.

Methods: We analyzed 7000 episodes reported by 1000 participants via crowdsourcing, using Japanese language parsers to extract time-related expressions. Each participant wrote seven episodes according to seven emotional stimulus words. Three participant groups were made according to their WHO-5 well-being index score. The high well-being score (WB) group and low-WB group were examined to assess time expression usage (high-WB group; WB ≥ 60, n = 367, mean WB = 70.6, std = 10.5: low-WB group; WB ≤ 40, n = 378, mean WB = 27.5, std = 11.4).
Results: Two-sided Fisher's exact test revealed that happy episodes with detailed time expressions are significantly more numerous in the high-WB group than in the low-WB group ($P = .001$), but no significant difference was found for any other pair.

Conclusions: Results show that vivid memories about a happy event are associated with mental well-being.

Keywords: Crowdsourcing; Narrative; Natural Language Processing, Mental Health

Introduction
Narrative research is generally approached qualitatively, but the development of information technology that can process natural language, such as speech recognition techniques and natural language processing techniques, have facilitated quantitative studies. Recently, several studies have been conducted with these technologies to elucidate quantitative aspects of human communication. A major challenge is development of a support tool for clinical decisions related to mental or physiological diseases. For quantitative studies, a core issue is to design a valid language clue that reflects the patients' state of a disease: idea density [1] is used for Alzheimer's disease screening [2], language difficulty is designed for autism spectrum disorder detection [3], and word connectedness is used for schizophrenia screening [4].

Among various language clues, two widely used linguistic features are overgenerality and specificity [5], which refer to the degree of abstraction of narratives. Overgeneral speech is typically observed with post-traumatic stress disorder (PTSD) [6]. Fundamentally, the specificity of an episode is assigned according to whether the participant mentions an event that happened in a moment, repetitions of events of the same kind, a certain period (e.g. the days when I was in the USA), or merely some individuals or things. Some researchers have investigated the degree of specificity using questionnaires [7]. The underlying mechanism is that the occurrence of trauma can change the mode of memory access, with trauma survivors learning to halt memory retrieval to avoid intense emotional distress. Reports obtained from patients with other mental disorders, not only PTSD, have also shown overgenerality, encouraging many related studies [8-10].

Our purpose is to develop an automatic tool to measure an individual's mental well-being. In this study, we use natural language processing (NLP) instead of manual analysis, aiming to measure an aspect of the specificity of an episode. From the viewpoint of NLP, specificity is easier to capture than overgenerality because the specificity of an episode should be broken down to some fixed grammatical categories such as proper nouns and date–time expressions. Generally in NLP, tasks related to specificity are classified into three types: (i) time-specification, (ii) location-specification, and (iii) name-specification. Among these three features, we specifically examine time expression, which is the easiest clue to capture.
We also strive to reveal the tendency of an individual to use time expressions based on their mental well-being, not on a particular psychological disorder. In the field of psychiatry, it is pointed out that positive mental health, which is also known as (mental) well-being, should be distinguishable from negative mental health [11-13]. From results of previous studies, overgeneral autobiographic memory was reported as associated with mental health difficulties such as depression and PTSD. Nevertheless, no report of the relevant literature describes a study of how well-being relates to the specificity of autobiographical memory. This study was conducted to ascertain the relation between positive mental health and the time specificity of autobiographic memory.

Methods

Ethics Statement

The use of these data for research purposes was approved by Yahoo! Crowdsourcing in accordance with the Japanese National Labour Law. The data contained no personally identifiable information, and written informed consent (including the waiver of copyrights) was obtained from all participants before analysis.

Statistical Analysis

Features

To elucidate the relation between time expression (TIMEXP) and well-being, we compared the tendencies of TIMEXP usage of two groups divided according to a well-being index. We found the frequency of episodes containing at least one TIMEXP, separately for stimulus words of emotion. Frequencies of TIMEXP in a broad and narrow sense (broad TIMEXP and narrow TIMEXP, respectively), which were extracted using a Japanese dependency and case structure analyzer, KNP parser [15], were found.

As the well-being index, we used the five-item World Health Organization Well-Being Index (WHO-5; hereinafter we use “WB” to refer to this well-being index score) [16], which is 0–100, used to screen psychological disorders rapidly. For example, the cut-off score of ≤ 50 on the WHO-5 is used for ‘screening diagnosis’ of depression. The cut-off score of ≤ 28 equals the level of well-being among patients with DSM-IV major depression. The use of the WHO-5 Well-Being Index is not limited to depression screening. It is also used to assess the variety of aspects including coping strategies and the association between workplace stress conditions and well-being.

Data Source

The data of this study were 7,000 short episodes, written in Japanese, related to personal experiences associated with some emotions. The episodes were collected from 1,000 Japanese participants through Yahoo! JAPAN Crowdsourcing [17] (See Figure 1 for questions pages on the website). We collected the episodes associated
with the following seven emotional words selected from the Plutchik’s wheel of emotions [18], which defines 8 basic emotions with each consists of three levels with accordance of its strength: sad, anxious, angry, hate, trustfull, surprise, and happy. To collect the episodes, we asked the following questions: “Please write the most impressive event in your life which evoked from the following word: [a word about emotion listed above].” Table 1 presents a translation of sample answers and descriptive statistics.

Table 1. Sample Answers and Basic Descriptive Statistics of the Data Episodes.

<table>
<thead>
<tr>
<th>emotion</th>
<th>sample answer</th>
<th>mean length (# of characters)</th>
<th>std of length (# of characters)</th>
</tr>
</thead>
<tbody>
<tr>
<td>sad</td>
<td>My pet died</td>
<td>15.60</td>
<td>25.97</td>
</tr>
<tr>
<td>anxious</td>
<td>The time my pet was ill</td>
<td>14.57</td>
<td>16.45</td>
</tr>
<tr>
<td>angry</td>
<td>I got angry at the manner of an insidious teacher</td>
<td>18.11</td>
<td>36.42</td>
</tr>
<tr>
<td>hate</td>
<td>Even a glance at the face of an insidious teacher disgusted me</td>
<td>17.54</td>
<td>23.33</td>
</tr>
<tr>
<td>trustful</td>
<td>I was trustful of a gentle senior student in my school</td>
<td>17.91</td>
<td>19.57</td>
</tr>
<tr>
<td>surprise</td>
<td>I accidentally met my acquaintance in the downtown</td>
<td>16.71</td>
<td>22.09</td>
</tr>
</tbody>
</table>
happy | far from my hometown I went to an amusement park with my family | 13.72 | 15.67

With these episodes, the participants also reported their WHO-5 Well-being Index score. After participants were divided into three groups according to the tertiles of the entire well-being index, we examined high-WB and low-WB groups: High-WB group (WB ≥ 60 (first tertile), n = 367, mean WB = 70.6, std = 10.5), low-WB group (WB ≤ 40 (second tertile), n = 378, mean WB = 27.5, std = 11.4).

**Data Processing**

The episodes were analyzed to extract linguistically defined time expressions using a morphological analyzer Juman ver. 7.01 [19], and dependency and case structure analyzer KNP ver. 4.16. After processing, TIMEXPs in an episode were identified by “time” tag and “strong-time” tag. In the other parts of this paper, an expression with a “time” tag is referred to as broad TIMEXP; the one with a “strong-time” tag is designated as narrow TIMEXP.

The “time” tag is assigned to a bunsetsu (a syntactic unit of Japanese language that usually consists of a combination of content words and functional words, longer than a word and shorter than a phrase) with nouns that describe time (e.g. “after school”, “the time when...”). However, “strong-time”, which is fundamentally a subcategory of “time” tag, is assigned to a bunsetsu with a time expression in a narrow sense (e.g. “at three”, “tomorrow”, “summer”, “by the time”, “so far”). More precisely, a “strong-time” tag is assigned to an expression that consists of [number + unit] (e.g. “five days”), [a noun referring to time + functional words] (e.g. “三時 (three) に (at)”), or [phrases indicating time limitation] (e.g. “until now”).

**Results**

**User Statistics**

To elucidate the relation between TIMEXP and well-being, we compared the tendencies of TIMEXP usage of two groups divided according to a well-being index. Figure 2 presents the frequency of episodes that include at least one TIMEXP, separately for stimulus words of emotion.
Figure 2. WB and Episodes with (a) broad TIMEXP and (b) narrow TIMEXP. The X-axis shows the kind of emotion associated with the episode. The Y-axis shows the ratio of episodes containing at least one broad TIMEXP. Red bars show the ratio of episodes written by the participants of high-WB group. Blue bars show the ratio of the low-WB group. Pairs with symbol * were found to be significantly different (p < 0.05).

We conducted two-sided Fisher’s exact test ($\alpha = 0.05$), which revealed that, as for broad TIMEXP, no significant difference was found for any pair. The tendency of the high-WB group to use a narrow TIMEXP in a happy episode was significantly higher than that of the low-WB group ($P = .001$), but the tendencies to use narrow TIMEXP in the episodes for other emotions did not differ significantly.

We also examined differences between high-WB group and low-WB group numbers of participants who used at least one TIMEXP in all episodes that a participant wrote. In the high-WB group, 222 of 367 (60.5%) participants used at least one broad TIMEXP; 136 of 367 (37%) participants used at least one narrow TIMEXP. In the low-WB group, 208 of 378 (55.0%) participants used at least one broad TIMEXP; 115 of 378 (30.4%) participants used at least one narrow TIMEXP. However, no significant difference was found using two-sided Fisher’s exact test ($\alpha = 0.05$).

**Discussion**

Results show that the frequencies of narrow TIMEXP are significantly different between the two groups, but only in happy episodes, which suggests that the kind of emotion associated with an episode is important, and that the time-specificity of an episode about a particular emotion reflects an individual’s mental state. Possible explanations of the reason are the following two: (i) Happy experiences that can be memorized as time-specific episodes affect mental well-being in later life. (ii) A person can remember details of happy episodes. Therefore, the individual’s mental well-being is high. In addition, the degree of specificity appears to be important for well-being.
For the experiment, we used two tags for time expressions (i.e. broad and narrow) to denote specificity. Only the frequencies of episodes with narrow TIMEXP were significantly different between the high-WB and low-WB groups. Results show that the high-WB participants described their happy memory with objective TIMEXP (e.g. “this summer” or “May fourth”), considering the characteristics of the two tags. Regarding narrow TIMEXPs in happy episodes, NLP techniques are effective clues to ascertain an individual’s well-being.

Time specificity in this study does not correspond precisely to that in earlier studies. It possibly influenced the results. In earlier studies, the degree of time specificity was classified along to the period that the episode describes. For example, “my high school graduation” was classified specifically because it describes an event that lasted less than one day, while “parties with my friends” and “when I was on vacation last month” were classified as overgeneral because they respectively describe a generic event and an event extending beyond one day [20]. However, in this study, the result of parsing “my high school graduation” includes no TIMEXP tags. That of “when I was on vacation last month” includes a narrow TIMEXP tag because of the mention of “last month.”

One contribution is that we identified a linguistic feature of a specific episode, and partly automated the detection of specific episodes. To date, the generality or specificity of an episode has been assessed manually by psychologists, or it has been self-reported. Nevertheless, manual assessment by a psychologist might be subjective or arbitrary. Moreover, self-reporting requires some participant effort, knowledge, and ability. Compared with such methods, the suggested method, which uses linguistic features in an episode, is more objective. It also requires less effort and no knowledge or ability.

Another characteristic of this study is that we used spontaneously reported information about time, by contrast to earlier studies in which participants were asked to report memories as specifically as possible. Although the method used in earlier studies would work well in an interactive environment such as a clinical interview, it might fail to reduce some information in detached situations, such as an application to develop an automatic diagnosis using an individual’s free speech. By contrast, our method employs features included in a spontaneously reported episode, providing a more natural environment.

Although our concept of specificity is slightly different from that suggested by Williams and Broadbent [5], we demonstrated that the difference in tendencies of high-WB and low-WB people to use specific time expressions can be detected using NLP technique. This study particularly examines time-specificity. However, using other specificities such as space and participant of an event would give more clues. More research using NLP will enable automatic detection of psychological disorders.
Acknowledgements
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Conflicts of Interest
None declared.

Abbreviations
NLP: natural language processing
PTSD: post-traumatic stress disorder
TIMEXP: time expression
WB: well-being score
WHO-5: five-item World Health Organization Well-Being Index

References