Embodied Emotions in Natural Language

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Abstract: (124/125 words max)
Emotions are often felt in the body, and embodiment is a prominent mechanism supporting language processing. Here we utilized computational linguistics to map embodied representations of emotions in a large corpus of English language. The data revealed consistent embodied patterns for emotion categories. Comparison of the semantics-derived versus self-reported bodily maps of emotions revealed similar, discrete bodily representations of different emotions in both texts and self-reports. Hierarchical clustering revealed three clusters: positive emotions in the head and chest, negative emotions in the torso and legs and negative social emotions mostly in the head. Replication in a Finnish corpus yielded consistent results. This data-driven analysis of embodied emotions in texts provides powerful means for mapping bodily emotions that aligns with the subjective embodiment of emotions.

Introduction

Emotions are core devices for storytelling. From *The Odyssey* to *Romeo and Juliet* and *The Catcher in The Rye*, we are drawn to the passions, desires, and fortunes of the fictional characters who are brought alive through our ability to transform written text into vivid and affect-imbued mental images of the imaginary worlds and their inhabitants. The core function of emotions is to prepare organisms for action by coordinating activity of the skeletomuscular, cardiorespiratory and endocrine systems to match with the current survival needs (*1–4*). Emotions are tightly linked with the homeostatic control of the body, and the brain responds continuously to the afferent visceral signals conveyed by the spinal and cranial nerves (*5*). The insular cortex represents autonomic responses and changes in visceral state and together with the amygdala and medial frontal cortex encodes the subjective emotional feelings, thus serving as the key hub for generating the subjective experience of emotion during both acute survival challenges as well as fictional affect-imbued episodes in written texts (*2*, *6*). Somatosensory cortices are also consistently activated during emotional behavior, and statistical pattern recognition studies have confirmed that an individual's current emotional state can be reliably "decoded" from the haemodynamic activity in the somatosensory cortex (*2*, *7*).

The bodily changes associated with emotions often trigger the subjective experience of emotion (such as "I am happy"). When hearing about the loss of our loved one we feel heavy-hearted, interpersonal conflicts make our minds blow with rage, while major victories and successes will make us feel proud and excited. Numerous studies have established that different emotions elicit discernible and culturally consistent "bodily feeling fingerprints", indicative of emotion-specific autonomic engagement (*3*, *8*, *9*). These bodily sensations are also translated to emotional language. Misfortunes in love lead to "broken hearts" while excitement and nervousness may bring "butterflies in the stomach", and a person filled with rage may be "bursting with anger". Embodied emotion theories propose that emotion concepts are grounded on the brain systems that generate visceral and motor states. When listening to emotional prose, the brain's emotional and somatosensory circuits closely track the emotional value of the language (*10–12*) and words describing actions executed with different body parts such as tongue (lick), hands (pick), and feet (kick), activate the somatotopic representation of the corresponding body parts in the motor strip (*13*). Similarly, sensorimotor activations in the brain's arm and leg regions are observed while participants process metaphors associated with arm ("she grasped the idea") or leg ("she kicked the habit") actions (*14*), highlighting the somatotopic precision of the embodied metaphor processing.

As bodily sensations associated with emotions influence our decisions from mundane everyday issues to passionate love and political divides (*15*, *16*), understanding how these embodied emotions are expressed in spoken and written language may help clarify how bodily experience is translated into concepts and communication. Although computational linguistic approaches such as sentiment analysis can be used for tracking the general affective value of narratives (*17*, *18*), they do not capture the quantitative associations between the emotional semantics and the textual embodiment patterns and bodily sensations. In other words, we do not know whether i) there exists emotion-specific regularities in the linkage between emotional and bodily language reflects the *de facto* emotion-specific coactivation patterns across bodily systems (*3*, *9*), rather than purely metaphorical communication of emotional states.

The current study

Recently, we have developed a new tool for mapping embodied emotions from texts based on the statistical regularities in co-occurrences between emotion words and different body parts (such as “disgust” → “stomach”; “fear” → “heart”). These regularities can be used for creating statistical parametric bodily maps or “feeling fingerprints” of emotions expressed in language (19). They represent the statistical probability of any given body part and an emotion word occurring in close proximity, thus indicating the semantic embodiment patterns for different emotions. Here we used this computational linguistic approach for mapping semantic representations of bodily emotions in a large English corpus, and compared the semantically derived maps with self-reported bodily maps of emotions. We first identified the occurrence of the most common words pertaining to emotions and body parts from the corpus, and used pointwise mutual information (PMI) embeddings to derive their co-occurrence patterns (19). These patterns were subsequently weighted by embeddings of emotion and body words and mapped on a 3D human model to create quantitative visualizations of the co-occurrence patterns. The weight maps were compared with self-reported bodily topographies of the same emotions from human subjects (n=101). The analytic approach is summarized in Figure 1. We show that a i) broad array (n=14) of emotions are associated with distinct bodily topographies in the written texts, ii) these bodily representations are consistent across occurrences of the emotions across the texts in the corpus and iii) that the bodily representations of emotions derived from the text match well with those reported by human subjects during the corresponding emotions and iv) that the semantic maps also generalize to an unrelated language (Finnish).

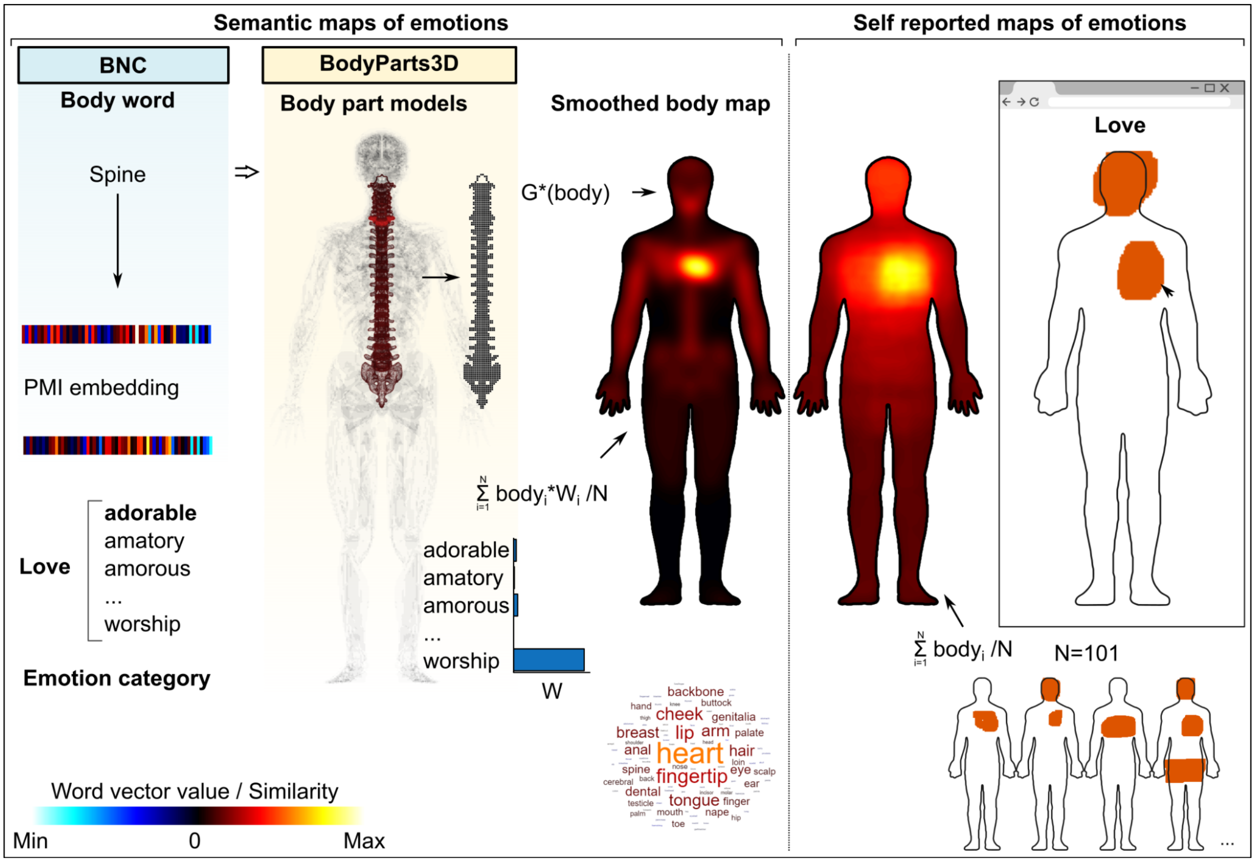

Figure 1 Semantic and self-reported maps of embodied emotions. *Semantic maps were created based on the cosine similarity of the pointwise mutual information (PMI) embeddings of body and emotions words based on the British national corpus (BNC; English). Similar analysis was repeated using the Finnish National Library's digitized newspaper and periodicals corpus (Finnish) to evaluate generalizability between language families. Self-reported body maps were generated with a web-based tool where participants painted, with the mouse, where in their body they experienced a set of emotion words. A population map was generated to reflect the mean rating and the reliability between subjects was analyzed to evaluate generalizability between individuals.*

Results

We first generated the average semantic maps of bodily emotions based on the corpus of and analysed their similarity structure (**Figure 2**). The bodily maps reflecting the maximum positive cosine similarity of a body part and all the emotion words belonging to the category revealed a clear categorical structure of the semantic bodily maps of emotions. Cluster analysis revealed three main clusters of the bodily maps. Positive emotions (happiness, love) formed one cluster, whereas negative emotions were split into one cluster consisting of negative social emotions (envy and contempt) while another comprised the basic negative emotions (fear, anxiety, depression, sadness, disgust, anger) and shame. Neutral emotional state, valence-wise ambiguous emotion surprise as well as pride remained independent of the main clusters.

We next tested how well the text-derived bodily maps of emotions correspond with self-reported bodily maps. **Figure 3** shows the resampled semantic and self-report body maps and histograms of the similarity of the semantic vs. self-report map of the same emotion compared to the similarities between the maps of different emotions. Visually the correspondence was on average high, which was also confirmed by the similarity metrics. Similarity between the semantic and self-reported body maps was on average $r=0.62$ and exceeded 0.5 for all categories except shame, sadness, and disgust.

To evaluate how well the category-wise emotion maps can be distinguished from each other or (i.e. how discrete the semantic and self-reported bodily "fingerprints" of emotions are), we performed nearest neighbor classification based on the semantic and self-report similarity matrices as well as the symmetrized inter-modality matrices. For these analyses, the bodily maps were mapped to vectors with one value for each body word included in the analyses. The accuracies of predicting the emotion categories are shown in **Fig 4** averaged over all emotion categories (**Fig 4A**) and separately for each emotion category (**Fig. 4B**). Corresponding mean confusion matrices across repeated classifications are shown in **Fig. 4C**. This analysis revealed that overall classifier performance exceeded chance level for both semantic and self-reported maps as well as for the intramodal classification, while classification accuracy was highest for the self-reported maps. Classification accuracy for individual emotions exceeded the chance level for all self-reported emotion maps and for all semantic emotion maps except for envy, indicating discrete bodily representations of emotions in both self-reports and semantics. Finally, cross-modal classification accuracy exceeded chance level for fear, depression, contempt, sadness, surprise, anger, and anxiety, indicating differences in the structural variability across the self-reports and semantic maps across emotions (despite significant spatial correlations across modality-specific maps shown in Figure 2). Equivalent analyses were repeated for the full 2-dimensional body maps (**Figure S1**), this led to poorer performance in the cross-modal classification demonstrating due to the different spatial scales across the modalities (i.e. detailed anatomy in the semantic maps versus approximate sensation localizations in the self-reports).

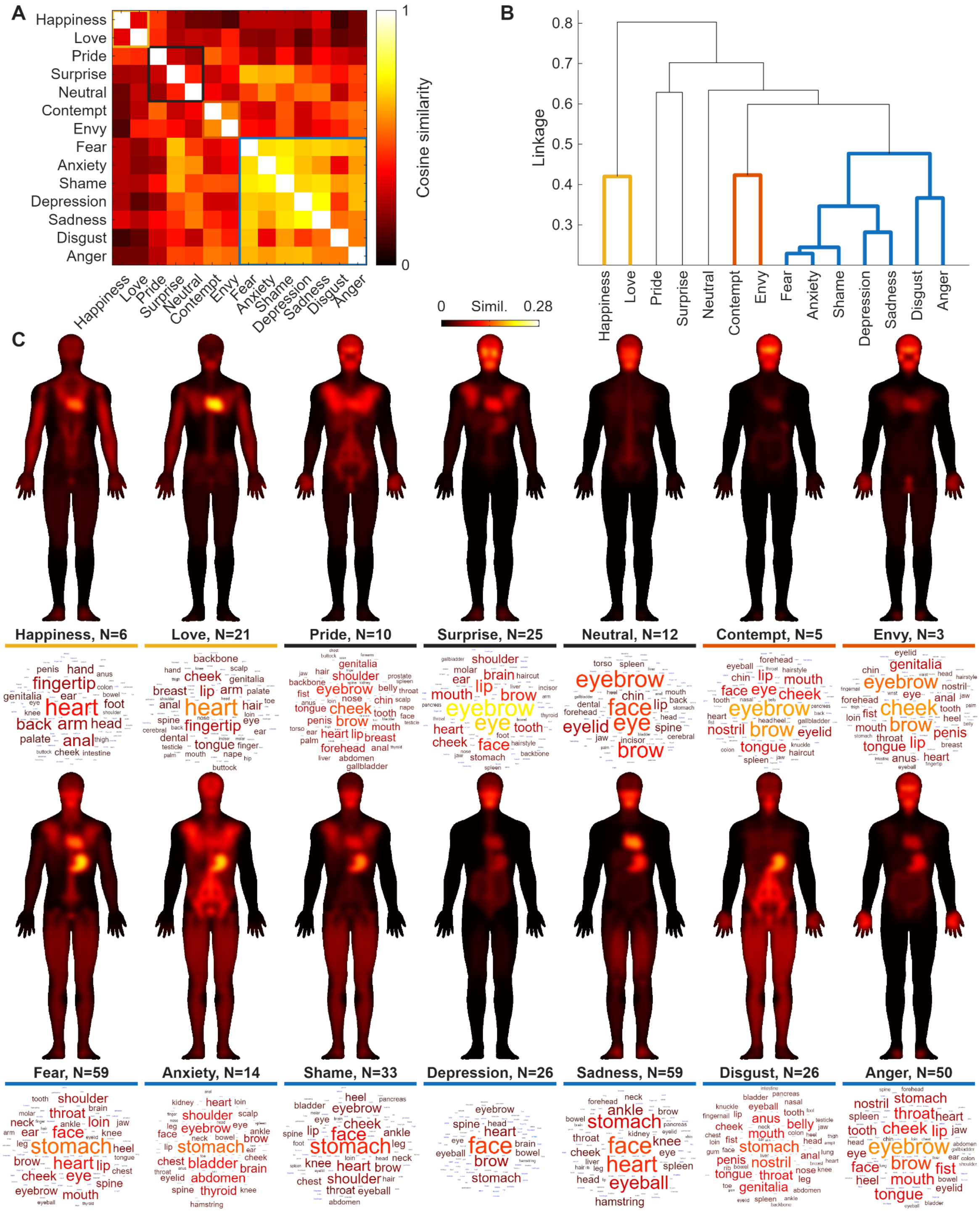

***Figure 2: Semantic maps of bodily emotions. A** Cosine similarity matrix of the mean vectors of emotion categories. **B** Dendrogram showing the hierarchical agglomerative clustering of the emotion categories.The most consistent clusters were color coded in yellow, red and blue, emotions not exceeding the cluster similarity threshold are shown in black. **C** Semantic maps of bodily emotions. The black-to-yellow colour coding body maps show the maximum positive cosine similarities between body parts and the emotion words included in each emotion category. The most frequently co-occurring body words are indicated by the word clouds below the body maps. The emotion categories are ordered by their proximity in a weighted average linkage hierarchical agglomerative clustering based on the cosine similarity of the weighted average vectors of the emotion categories. The emotion categories in all panels are ordered and the clusters are indicated by colored lines based on the cluster solution in panel B.*

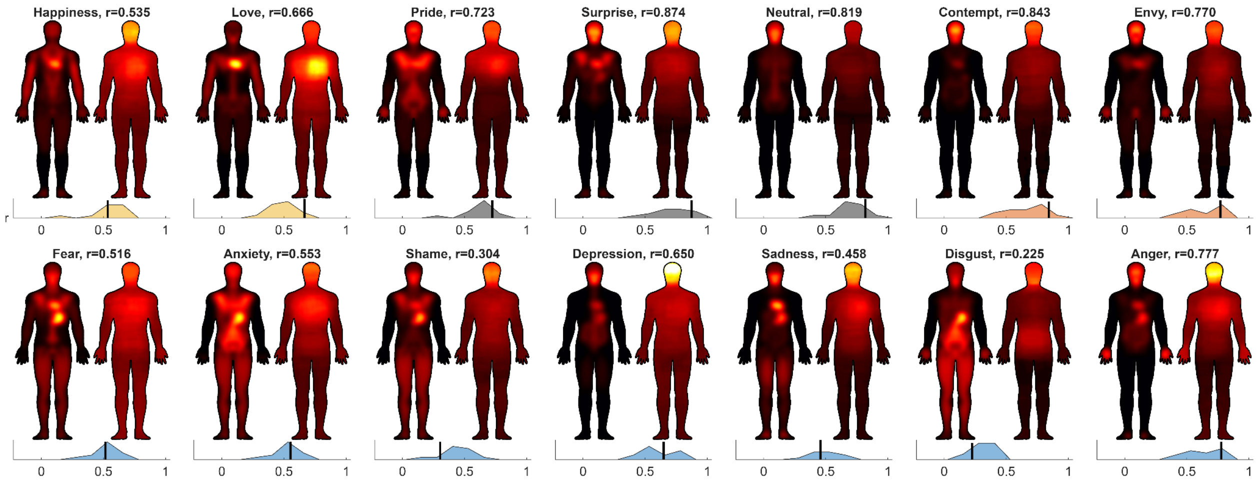

Figure 3: Semantic and self-report bodily maps of emotions. *For each emotion category, the figure shows the body maps based on semantic cosine similarity of body and emotion words (left) and the self-reported bodily feelings associated with emotions (right) sampled into the same 2D space. The spatial correlation of the semantic vs. self-report maps are shown above each body map. The similarity distributions of the self-report and semantic maps are shown below the body maps with the thick vertical line indicating the similarity of the maps for the same category. The similarity distributions indicate the symmetrized pairwise similarities of the mean of self-report vs. semantic body maps. The order of emotions and the colors of the similarity distributions reflect the clustering solution in Figure 2B.*

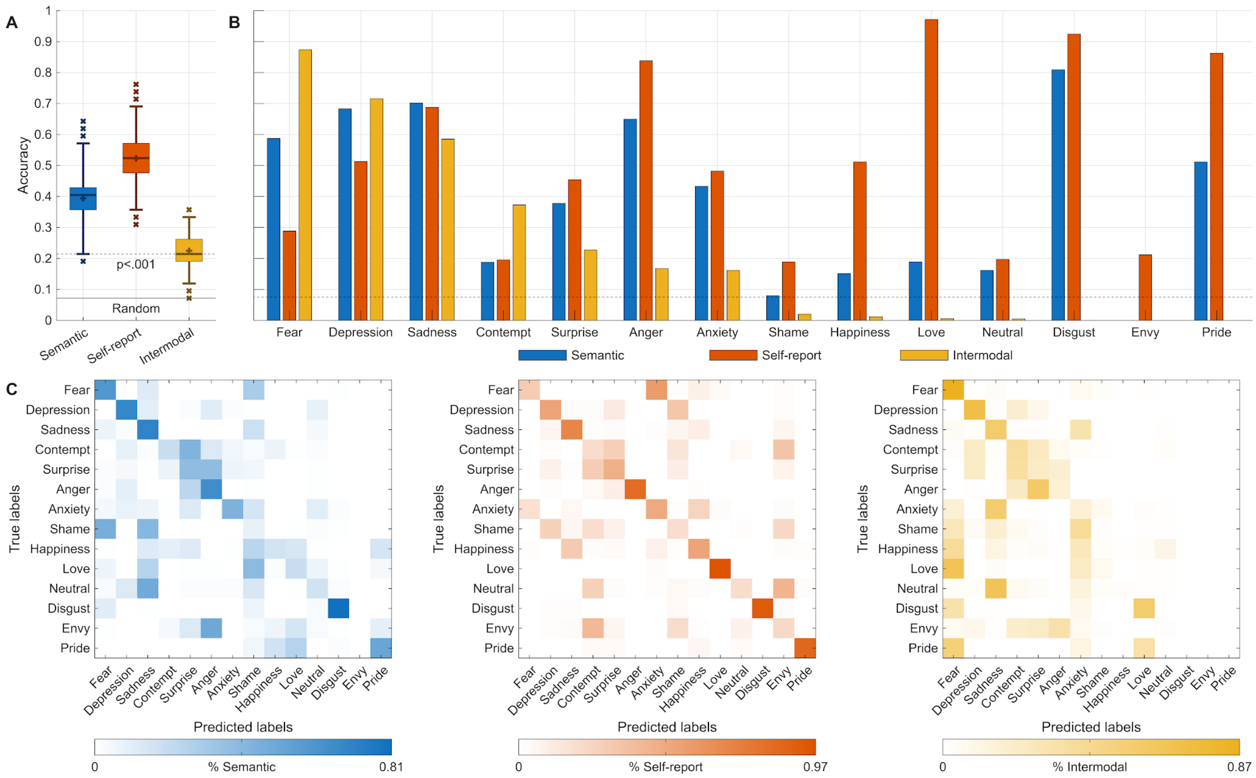

Figure 4: Classification accuracy for bodily maps of emotions within and across modalities. *A: Overall classification accuracy for semantic maps (blue), self-reported maps (orange) and crossmodal classification.* ***B*** *Emotion-specific classification accuracies or* ***C*** *Confusion matrices of semantic, self-report and intermodal classification, respectively. Color coding is indicated on the x-axis of panel and in the legend below the panel. Accuracies are based on 3-fold nearest neighbor classification based semantic, self-report and symmetrized inter-modality correlation matrices and the associated null accuracies with randomized labels. Thresholds based on null analyses are indicated by dashed black lines in panels A and B (A p<.001 across iterations, B maximum accuracy across categories). The theoretical random accuracy (p=1/14) is indicated by the solid black line in panel A. Emotions are sorted based on their intermodal identification accuracy (yellow bars).*

Although the embodiment of the emotions in the large English corpus matched well with the actual bodily sensations with are known to be culturally universal (*8*, *9*) it is possible that this linkage is of different magnitude in other languages that potentially have less precise mapping between *de facto* emotions and bodily responses and that our results would be specific to the English language (*19*, *20*). To address this issue, we conducted a replication analysis for the semantic bodily mapping in Finnish - an Uralic language unrelated to Indo-European languages (including English). We extracted the same years (1960–1993) from the Finnish National Library's digitized newspaper and periodicals corpus as in the main analysis based on the BNC corpus (see **SI file** for details) and generated the semantic bodily maps using same workflow and parameters as for the English data. This revealed remarkable consistency across the semantic body maps across the languages (mean similarity r = 0.59; see **Figure S2**). Prediction accuracy between languages was also significantly above chance level (mean accuracy .31 across emotion categories vs. .07 by chance) and was particularly successful for disgust (.77), surprise (.69) and depression (.54). By contrast, sadness, envy, neutral and anxiety were confused with other emotion categories (for confusion matrices within and between languages, see **Figure S3**).

Discussion

Our main findings were that bodily representations of a wide array of emotions (n=14) can be automatically derived from a large corpus of written text. These bodily signatures were discrete, as evidenced by the above-chance-level classification of the emotion-specific bodily maps. The semantics-derived bodily maps of specific emotions also corresponded well with those reported by human subjects while experiencing the same emotions. Altogether these data support the discrete representation of embodied emotions in written texts, and highlight how semantic descriptions of emotions in natural language reflect the bodily basis of emotions (*3*, *8*, *21*).

Bodily maps of emotional semantics

Analysis of the statistical co-occurrence between body words and emotions yielded distinct maps for the tested emotions. Statistical testing confirmed that the emotion-body word pairings were consistent across emotion word instances for each emotion, indicating regularity in the way different emotions are described in texts (**Fig 1**). Both classic and modern emotion theories posit that subjective emotional feelings are at least partially determined by emotion-related changes in the skeletomuscular, neuroendocrine, and autonomic nervous systems (*3*, *22*, *23*). Previous studies based on self-reported bodily sensations evoked by emotions has confirmed that different emotions are associated with distinctive "feeling fingerprints" that are consistent across individuals while they are exposed to a wide array of potentially emotion-evoking material ranging from videos, narrative texts, visual art, and music (*3*, *8*, *24*). The present study goes significantly beyond this line of work by revealing that the bodily feeling topographies can be derived computationally from the text corpus. In other words, the links between different emotions and body parts are described consistently across occurrences in texts, indicating a consistent semantic embodiment of emotions. Replication analysis in an independent corpus from an unrelated Uralic language (Finnish) yielded consistent semantic maps of bodily emotions. Although this similarity does not rule out the possibility that the semantic emotional mapping could diverge from the *de facto* sensation patterns in *some* languages, it provides strong evidence against the cultural specificity of our findings, as similar emotional embeddings are consistently observed across distinct languages (Uralic Finnish and Indo-European English) and text corpora. The visceral and autonomic changes of emotions are a universally shared human experience whose efficient communication has warranted shared linguistic reference, thus likely resulting in comparable mappings between emotions and their bodily constituents across languages.

Major categorical theories of emotion have argued that different emotions (such as anger, fear, disgust etc) prepare the organisms for different survival challenges, and thus are accompanied by discrete changes in autonomic and neural activity (*25–27*). Our data provide support for the categorical model of emotions on the level of the semantic descriptors of bodily emotions. Emotion-related language informed by the physiological, emotion-related bodily activations is also consistently discrete across emotions, so that different emotions occur systematically with different constellations of body parts and regions in natural language. The computationally derived "feeling fingerprints" of different emotions are visually saliently different across different emotions. For example, love was profoundly associated with activity in the chest, disgust with stomach, and anger with upper limbs. This discreteness was also confirmed formally using statistical pattern recognition. All the semantic bodily maps of emotions (except envy) could be classified from each other significantly above chance level, confirming their independence. Semantic descriptions of emotion-evoked bodily changes are thus discrete and consistent within each emotion category, as otherwise successful training of the classifier as well as predicting the emotion categories in the independent test data sets would not have been possible. In other words, writers describe emotion-specific bodily responses differently and categorically depending on the emotion, most likely due to the consistent differences in the emotion-evoked autonomic and visceral activation patterns.

Semantic bodily emotions correspond with self-reports

Our data confirmed that the semantic bodily maps of emotions closely correspond with bodily maps of self-reported emotional experiences gathered from human volunteers. This was evidenced by the high spatial correlations (mean $r > 0.62$) between the semantic and self-reported body maps, suggesting that texts containing references to different emotions also contain semantic descriptions of the same bodily parts that people report being activating when experiencing these emotions (**Fig 3**). Correspondence between the semantic and self-reported body maps was also supported by the cross-classification of the body maps, where the classifier was first trained on the semantic maps and tested on the self-reported maps, or *vice versa*. Overall this approach yielded above chance level mean accuracy of 0.22 against chance level of 0.07, and exceeding more conservative permutation based null accuracy of individual iterations (0.21, $p<.001$) ** Juha can we have the exact numbers **. However, unlike the within-modality classifiers (train with semantic maps – test with semantic maps and train with self-reported maps – test with self-reported maps) which yielded above chance level accuracy for practically all emotions, the cross-classification accuracy was not equally high for all emotions and particularly shame, contempt and envy (and the neutral emotional state) tended to be misclassified as fear. This likely reflects the overall weak linkage between emotional and bodily semantics for these emotions in the semantic maps. Thus, the mapping of subjective emotional sensations to bodily responses in texts is not perfect and the accuracy is emotion-dependent. Yet, we stress that despite these discrepancies across data types for certain emotions, the semantically derived body maps were discrete and consistent across occurrences of the emotion words.

It could be argued that both the semantic and bodily maps of emotions simply reflect cultural conventions or social schemata in describing the relationship between emotions and body parts through, for example, figurative expressions in English language such as “cold feet” or "butterflies in stomach” (*28*, *29*). For the self-reported body maps this is unlikely given the high consistency of the self-reported emotions (*30*) and bodily signatures of emotions across cultures and languages (*3*, *9*) even when bodily sensation patterns to non-linguistic emotional material such as music are measured (*8*). These subjective sensations thus reflect universal sensation patterns brought about by emotion systems, which must be based on biological associations between the emotions and the sensations. Given the i) consistency of the self-reported and semantic maps and ii) consistency in the semantic bodily maps of emotions across languages, we argue that our results show that the conventions of referring to specific body parts in relation to specific emotions in language arise from the consistent mapping between consciously accessible bodily sensations triggered by different emotions, that are in turn reflected in the way we write about emotions. In other words, our emotions shape the way we write about emotions, rather than vice versa.

Limitations and future directions

The study was run using English and Finnish corpora with primarily late 20th-century texts. Thus the results may not generalize to other languages. The used corpus contained texts from different genres (English: 85,162,735 words in 1,411 books and 1,208 periodicals, Finnish: 464,019,962 words in 18 periodicals and newspapers), yet we deliberately did not split the data between genres such as fiction versus media articles to ensure generalizability and statistical power. Future studies could extend this work using corpora focused on specific genres such as News on Web and Wikipedia Corpus that contain more selective text sources to address the potential context-dependency of embodied emotions in language. Using corpora spanning longer time windows would also allow investigating whether the semantic embodied representation of emotion varies across time, cultures, as well as text types. Although cultural universality in the bodily experience of emotions has been well established (*8*, *9*) the semantic descriptors of the bodily basis of emotions may not be immutable over time. For example, limited understanding of human physiology and psychology based on religious beliefs in early cultures or the nature of genres of texts in the corpora (e.g., medical, religious, and administrative texts) could affect the way emotions are described in historic texts (*31*, *32*). Finally, the patterns established through the PMI embeddings do not account for the context in which the body parts and the emotions co-occur. For example, statements such as “I was so scared that my heart was racing” and “I was so much in love that my heart was melting” contain similar mutual information between “heart” and the emotion words “love” and “scared” despite the context and the described cardiac physiology being completely different. However, similar unspecificity also applies to the self-reported topographies of bodily emotions (*21*), and despite this unspecificity the data revealed discrete semantic bodily maps across different emotions, as well as concordance between semantic and self-reported bodily maps.

Conclusions

We conclude that semantic representations of different embodied emotions are discrete and align with the subjective experience of the emotions in the body. This data-driven analysis provides a method for mapping how bodily aspects of emotion are represented in natural language. Emotions play a central role in stories: they motivate characters’ actions, engage readers, and can shape readers’ interpretations and attitudes (*33*, *34*). Given the centrality of the somatic sensations in generating subjective emotions and guiding decision making (*3*, *5*, *15*), this approach provides powerful means for mapping the affective impact of literature, news, and social media.

References

1. L. Nummenmaa, H. Saarimäki, Emotions as discrete patterns of systemic activity. *Neuroscience Letters*, doi: 10.1016/j.neulet.2017.07.012 (2017).

2. H. Saarimäki, A. Gotsopoulos, I. P. Jääskeläinen, J. Lampinen, P. Vuilleumier, R. Hari, M. Sams, L. Nummenmaa, Discrete Neural Signatures of Basic Emotions. *Cereb. Cortex* **6**, 2563–2573 (2016).

3. L. Nummenmaa, E. Glerean, R. Hari, J. K. Hietanen, Bodily maps of emotions. *Proc. Natl. Acad. Sci. U. S. A.* **111**, 646–651 (2014).

4. R. W. Levenson, "Blood, sweat, and fears - The autonomic architecture of emotion" in *Emotions inside Out: 130 Years after Darwin's the Expression of the Emotions in Man and Animals*, Ekman, P. Campos, J. J. Davidson, R. J. DeWaal, F. B. M., Ed. (New York Acad Sciences, New York, 2003)vol. 1000 of *Annals of the New York Academy of Sciences*, pp. 348–366.

5. A. D. Craig, How do you feel? Interoception: the sense of the physiological condition of the body. *Nat. Rev. Neurosci.* **3**, 655 (2002).

6. H. D. Critchley, S. Wiens, P. Rotshtein, A. Ohman, R. J. Dolan, Neural systems supporting interoceptive awareness. *Nat. Neurosci.* **7**, 189–195 (2004).

7. H. Saarimäki, L. F. Ejtehadian, E. Glerean, I. P. Jaaskelainen, P. Vuilleumier, M. Sams, L. Nummenmaa, Distributed affective space represents multiple emotion categories across the human brain. *Social cognitive and affective neuroscience* **13**, 471–482 (2018).

8. V. Putkinen, X. Zhou, X. Gan, L. Yang, B. Becker, M. Sams, L. Nummenmaa, Bodily maps of musical sensations across cultures. *Proc. Natl. Acad. Sci. U. S. A.* **121**, e2308859121 (2024).

9. S. Volynets, E. Glerean, J. K. Hietanen, R. Hari, L. Nummenmaa, Bodily maps of emotions are culturally universal. *Emotion*, doi: 10.1037/emo0000624 (2019).

10. L. Nummenmaa, H. Saarimäki, E. Glerean, A. Gotsopoulos, I. P. Jääskeläinen, R. Hari, M. Sams, Emotional speech synchronizes brains across listeners and engages large-scale dynamic brain networks. *Neuroimage* **102 Pt 2**, 498–509 (2014).

11. E. Komulainen, E. Glerean, K. Meskanen, R. Heikkilä, L. Nummenmaa, T. T. Raij, J. Lahti, P. Jylhä, T. Melartin, E. Isometsä, J. Ekelund, Single dose of mirtazapine modulates whole-brain functional connectivity during emotional narrative processing. *Psychiatry Res. Neuroimaging* **263**, 61–69 (2017).

12. M. Wallentin, A. H. Nielsen, P. Vuust, A. Dohn, A. Roepstorff, T. E. Lund, Amygdala and heart rate variability responses from listening to emotionally intense parts of

a story. *Neuroimage* **58**, 963–973 (2011).

13. O. Hauk, I. Johnsrude, F. Pulvermüller, Somatotopic representation of action words in human motor and premotor cortex. *Neuron* **41**, 301–307 (2004).

14. V. Boulenger, O. Hauk, F. Pulvermüller, Grasping ideas with the motor system: semantic somatotopy in idiom comprehension. *Cereb. Cortex* **19**, 1905–1914 (2009).

15. A. Bechara, A. R. Damasio, The somatic marker hypothesis: A neural theory of economic decision. *Games Econ. Behav.* **52**, 336–372 (2005).

16. M. Tsakiris, N. Vehar, R. Tucciarelli, Visceral politics: a theoretical and empirical proof of concept. *Philos. Trans. R. Soc. Lond. B Biol. Sci.* **376**, 20200142 (2021).

17. P. Nandwani, R. Verma, A review on sentiment analysis and emotion detection from text. *Soc. Netw. Anal. Min.* **11**, 81 (2021).

18. D. Rozado, R. Hughes, J. Halberstadt, Longitudinal analysis of sentiment and emotion in news media headlines using automated labelling with Transformer language models. *PLoS One* **17**, e0276367 (2022).

19. K. A. Lindquist, J. C. Jackson, J. Leshin, A. B. Satpute, M. Gendron, The cultural evolution of emotion. *Nat. Rev. Psychol.* **1**, 669–681 (2022).

20. J. C. Jackson, J. Watts, T. R. Henry, J.-M. List, R. Forkel, P. J. Mucha, S. J. Greenhill, R. D. Gray, K. A. Lindquist, Emotion semantics show both cultural variation and universal structure. *Science* **366**, 1517–1522 (2019).

21. L. Nummenmaa, R. Hari, J. K. Hietanen, E. Glerean, Maps of subjective feelings. *Proc. Natl. Acad. Sci. U. S. A.* **115**, 9198–9203 (2018).

22. A. Damasio, G. B. Carvalho, The nature of feelings: evolutionary and neurobiological origins. *Nat. Rev. Neurosci.* **14**, 143–152 (2013).

23. W. James, What is an emotion? *Mind* **9**, 188–205 (1884).

24. L. Nummenmaa, R. Hari, Bodily feelings and aesthetic experience of art. *Cogn. Emot.*, 1–14 (2023).

25. P. Ekman, An argument for basic emotions. *Cognition & Emotion* **6**, 169–200 (1992).

26. A. S. Cowen, D. Keltner, Self-report captures 27 distinct categories of emotion bridged by continuous gradients. *Proceedings of the National Academy of Sciences*, doi: 10.1073/pnas.1702247114 (2017).

27. T. Horikawa, A. S. Cowen, D. Keltner, Y. Kamitani, The Neural Representation of Visually Evoked Emotion Is High-Dimensional, Categorical, and Distributed across

Transmodal Brain Regions. *Iscience* **23**, 43 (2020).

28. B. Rimé, P. Philippot, D. Cisamolo, Social schemata of peripheral changes in emotion. *J. Pers. Soc. Psychol.* **59**, 38–49 (1990).

29. P. Heelas, "Emotion talk across cultures" in *The Emotions* (Routledge, London, 2007), pp. 31–36.

30. A. S. Cowen, X. Fang, D. Sauter, D. Keltner, What music makes us feel: At least 13 dimensions organize subjective experiences associated with music across different cultures. *Proc. Natl. Acad. Sci. U. S. A.* **117**, 1924 (2020).

31. J. M. Lahnakoski, E. Bennett, L. Nummenmaa, U. Steinert, M. Sams, S. Svärd, Embodied emotions in ancient Neo-Assyrian texts revealed by bodily mapping of emotional semantics. *iScience* **27**, 111365 (2024).

32. S. Svärd, T. Alstola, H. Jauhiainen, A. Sahala, K. Lindén, "Fear in akkadian texts: New digital perspectives on lexical semantics" in *The Expression of Emotions in Ancient Egypt and Mesopotamia* (BRILL, 2020), pp. 470–502.

33. A. J. Reagan, L. Mitchell, D. Kiley, C. M. Danforth, P. S. Dodds, The emotional arcs of stories are dominated by six basic shapes. *EPJ Data Sci.* **5** (2016).

34. J. R. Winkler, M. Appel, M.-L. C. R. Schmidt, T. Richter, The experience of emotional shifts in narrative persuasion. *Media Psychol.*, 1–31 (2022).

35. C. Strapparava, A. Valitutti, WordNet Affect: an Affective Extension of WordNet. *LREC* (2004).

36. S. Tuovila, "Kun on tunteet," thesis, University of Oulu, Oulu, Finland (2005).

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