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Brief Communications

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Leveraging natural language processing and machine learning to characterize psychological stress and life meaning and purpose in pediatric cancer survivors: a preliminary validation study

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Abstract

Objective: To determine if natural language processing (NLP) and machine learning (ML) techniques accurately identify interview-based psychological stress and meaning/purpose data in child/adolescent cancer survivors.

Materials and Methods: Interviews were conducted with 51 survivors (aged 8-17.9 years; ≥5-years post-therapy) from St Jude Children's Research Hospital. Two content experts coded 244 and 513 semantic units, focusing on attributes of psychological stress (anger, controllability/manageability, fear/anxiety) and attributes of meaning/purpose (goal, optimism, purpose). Content experts extracted specific attributes from the interviews, which were designated as the gold standard. Two NLP/ML methods, Word2Vec with Extreme Gradient Boosting (XGBoost), and Bidirectional Encoder Representations from Transformers Large ($BERT_{Large}$), were validated using accuracy, areas under the receiver operating characteristic curves (AUROCC), and under the precision-recall curves (AUPRC).

Results: $BERT_{Large}$ demonstrated higher accuracy, AUROCC, and AUPRC in identifying all attributes of psychological stress and meaning/purpose versus Word2Vec/XGBoost. $BERT_{Large}$ significantly outperformed Word2Vec/XGBoost in characterizing all attributes ($P<.05$) except for the purpose attribute of meaning/purpose.

Discussion: These findings suggest that AI tools can help healthcare providers efficiently assess emotional well-being of childhood cancer survivors, supporting future clinical interventions.

Conclusions: NLP/ML effectively identifies interview-based data for child/adolescent cancer survivors.

Lay Summary

Understanding the psychological well-being of childhood cancer survivors is important for improving their long-term well-being. This study explored whether artificial intelligence (AI) techniques, specifically natural language processing (NLP) and machine learning (ML), can accurately analyze interviews to detect signs of psychological stress and a sense of meaning or purpose in survivors. Researchers conducted interviews with 51 childhood cancer survivors, aged 8-17.9 years, who were at least 5 years post-treatment. Experts manually analyzed the interviews to identify expressions of stress (anger, anxiety, and control over emotions) and meaning/purpose (optimism, goals, and a sense of purpose). These expert-coded results served as the gold standard for evaluating AI models. Two AI methods were tested: Word2Vec with XGBoost and $BERT_{Large}$. The findings showed that $BERT_{Large}$ was more accurate in identifying stress and meaning-related expressions compared to Word2Vec/XGBoost. $BERT_{Large}$ significantly outperformed Word2Vec/XGBoost in detecting all attributes. These results suggest that AI-driven tools can effectively analyze interview data, potentially helping healthcare providers assess the emotional well-being of childhood cancer survivors more efficiently. This approach may enhance future interventions to support survivors' mental health.

Key words: machine learning; meaning and purpose; natural language processing; patient-reported outcomes; pediatric cancer survivors; psychological stress.

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Introduction

Children diagnosed with cancer experience significant disruptions in daily life and psychological stress, both during treatment and throughout survivorship.[1] Systematic reviews highlight the prevalence of psychological challenges in childhood cancer survivors, with up to 35% reporting stress related to their cancer experience.[2] For a subset of survivors, psychological burden may arise from the challenges of coping during treatment and adapting to the ongoing changes associated with survivorship.[3–5]

Finding meaning and purpose in life (or psychological growth) can ameliorate psychological distress, help survivors develop resilience after their cancer experiences, and contribute to positive personal growth.[6–9] Research indicates that a stronger sense of meaning/purpose and reduced psychological stress are associated with improved quality-of-life[7,10] and higher survival rates.[11–13] Assessing survivors' psychological stress and life purpose offers valuable implications for survivorship care beyond traditional clinical data. However, these issues remain underexplored, especially among survivors under 18 years of age in the early post-treatment stage.[9]

Collecting patient-reported outcomes (PROs) via surveys within a busy clinical setting has been challenging, especially since psychological stress and meaning/purpose in life are multifaceted constructs encompassing a range of interrelated concepts.[14] Incorporating data collection on psychological stress and meaning/purpose topics into physician-patient conversations or semi-structured interviews during clinical encounters could serve as a complementary approach, enriching the depth and utility of traditional survey-based methods.

Analyzing qualitative PROs is challenging due to their unstructured nature and complexity, yet it offers valuable insights for delivering personalized care to survivors. Advanced methodologies, leveraging natural language processing (NLP) and machine learning (ML), enable extracting meaningful information into psychological stress and sense of purpose from large volumes of qualitative PROs.

To advance the clinical application of qualitative PROs, this study utilized NLP and ML techniques to analyze the psychological stress and meaning/purpose concepts through interviews with child and adolescent cancer survivors. The accuracy of these NLP/ML algorithms was validated by comparing their outputs to expert-coded findings, which served as the gold standard.

Methods

Study participants

Clinical Research Associates with extensive interview experiences conducted semi-structured interviews with childhood cancer survivors and their caregivers at the After Completion of Therapy Clinic of St Jude Children's Research Hospital (hereafter "SJCRH") in the United States. We recruited survivors aged 8-17 years who were at least 2 years post-therapy and 5 years from their initial cancer diagnosis. We collected data on perceived psychological stress from 53 participants. We transcribed the interview data and extracted 244 semantic units from the psychological stress interviews and 513 semantic units from the meaning/purpose interviews. Assent was obtained from the survivors, and consent was obtained from their caregivers before study participation. The SJCRH's institutional review board reviewed and approved the study protocol.

Qualitative interview and data extraction

We designed 2 qualitative interview guides, each with specific probes, to explore PROs in the domains of psychological stress and meaning/purpose.[8] The interview guides are provided in the Supplementary Data S1 section on the journal's website. We defined psychological stress as a child's negative thoughts or emotions about themselves and their surroundings in response to internal or external challenges,[15] and meaning/purpose as a child's sense of life satisfaction, hopefulness, and direction, reflecting their ability to find value and set goals in their experiences.[6,16] After completing the interviews, we transcribed the audio recordings verbatim and extracted meaningful semantic units, defined as meaningful and interpretable sentences.

Expert labeled coding

Using the established PROMIS framework, 2 content experts (J.L.C. and C.M.J.) coded each PRO domain (psychological stress and meaning/purpose) into meaningful semantic units.[17,18] For the psychological stress domain, semantic units were assigned to a specific attribute, including anger, controllability/manageability, and fear/anxiety. Specific attributes extracted from the interviews by content experts were considered the gold standard. For the meaning/purpose domain, semantic units were assigned to a specific attribute, including goal orientation, optimism, and purpose. For example, in the psychological stress domain, when a survivor stated, "I was stressing out because I didn't know how to prepare for the reading FSA [test]," this semantic unit was mapped to the concept "Felt stressed" and labeled under the attribute of controllability/manageability. Similarly, in the meaning/purpose domain, when a survivor stated, "The goal of being a nurse is from having cancer. I just like to help other kids who are, went through the same kind of things I went through," this unit was mapped to the concept "have a goal for future" and labeled under the attribute of goal orientation.

NLP/ML techniques and statistical testing

We used NLP and NL techniques (combining Word2vec combined with Extreme Gradient Boosting [XGBoost])[19,20] and NLP techniques (Bidirectional Encoder Representations from Transformers Large [$BERT_{Large}$][21]) to analyze the semantic attributes. Word2Vec is a shallow neural network for word embeddings, requiring NLP and ML to extract semantic relationships, while $BERT_{Large}$ is a deep transformer-based model for automated text analysis that captures contextual meanings, identifies patterns, and extracts relationships to enhance language interpretation accuracy.

The performance of the NLP/ML models was evaluated using standard metrics, including sensitivity (recall) as true positives/(true positives+false negatives), specificity as true negatives/(true negatives+false positives), accuracy as (true positives+true negatives)/total samples, the area under the receiver operating characteristic curve (AUROCC) as plot of true positive rate versus false positive rate across thresholds, and the area under the precision-recall curve (AUPRC) plot of precision versus recall across thresholds. We implemented a 5-fold nested cross-validation for final validation within the training and testing datasets. DeLong's test was used to compare AUROCC and AUPRC values, while 95% confidence intervals were calculated via bootstrapping to provide a robust evaluation of performance differences between Word2Vec/XGBoost $BERT_{Large}$ in characterizing attributes of the 2 PRO domains.

Results

Participant characteristics

Among study participants, the mean (SD) ages at the time of interviews were 14.1 ± 2.8 years, 61% were females, and approximately 42% were treated for noncentral nervous system solid tumors and 33% for leukemia.

Model performance: sensitivity, specificity, and accuracy

Table 1 summarizes the performance of 2 NLP/ML models (Word2Vec/XGBoost and $BERT_{Large}$) for characterizing related attributes within the 2 PRO domains. For the sensitivity metric, $BERT_{Large}$ outperformed Word2Vec/XGBoost in characterizing all 3 attributes for the psychological stress domain and all 3 attributes for the meaning/purpose domain. For the specificity metric, both methods achieved values greater than 0.9 across all attributes, except for the controllability/manageability attribute within the psychological stress domain (Word2Vec/XGBoost: 0.82, $BERT_{Large}$: 0.83). $BERT_{Large}$ better classified anger and controllability/manageability attributes for the psychological stress domain and the purpose attribute for the meaning/purpose domain. Conversely, Word2Vec/XGBoost better classified the fear/anxiety attribute in the psychological stress domain and the goal orientation and optimism attributes in the meaning/purpose domain.

$BERT_{Large}$ demonstrated high accuracy values across 3 attributes, exceeding 0.7. Specifically, the values were 0.894 (95% CI: 0.857-0.935), 0.743 (95% CI: 0.686-0.796), and 0.848 (95% CI: 0.802-0.889) for the anger, controllability/manageability, and fear/anxiety attributes in the psychological stress domain, respectively. For the meaning/purpose domain, the values were 0.856 (95% CI: 0.825-0.885), 0.860 (95% CI: 0.830-0.889), and 0.836 (95% CI: 0.807-0.869) for the goal orientation, optimism, and purpose attributes, respectively.

Model performance: AUROCC

The upper section of Figure 1A and B displays the highest AUROCC achieved by the NLP/ML method for each of the 6 attributes across 2 PRO domains (detailed in Table 1). In the psychological stress domain (left panel), the $BERT_{Large}$ model demonstrated higher AUROCC values compared to the Word2Vec/XGBoost model, with 0.888 (95% CI: 0.820-0.963) for the anger attribute, 0.768 (95% CI: 0.707-0.817) for the controllability/manageability attribute, and 0.827 (95% CI: 0.757-0.897) for the fear/anxiety attribute. Similarly, in the meaning/purpose domain (right panel), the $BERT_{Large}$ model demonstrated higher AUROCC values compared to the Word2Vec/XGBoost model, with 0.848 (95% CI: 0.815-0.900) for the goal attribute and 0.729 (95% CI: 0.649-0.797) for the optimism attribute. Differential comparisons showed that $BERT_{Large}$ significantly outperformed Word2Vec/XGBoost in characterizing the goal attribute within the meaning/purpose domain ($P < .05$; Table 2).

Model performance: AUPRC

The lower section of Figure 2A and B illustrates the highest AUPRC achieved by the NLP/ML method for each of the 6 attributes across 2 PRO domains (detailed in Table 1). In the psychological stress domain (left panel), the $BERT_{Large}$ model demonstrated higher AUPRC values compared to the Word2Vec/XGBoost model, with values of 0.802 (95% CI: 0.701-0.886) for the anger attribute, 0.696 (95% CI: 0.611-0.783) for the controllability/manageability attribute, and 0.723 (95% CI: 0.638-0.848) for the fear/anxiety attribute. Similarly, in the meaning/purpose domain (right panel), the $BERT_{Large}$ model demonstrated higher AUPRC values compared to the Word2Vec/XGBoost model, with 0.645 (95% CI: 0.553-0.735) for the goal attribute, 0.503 (95% CI: 0.370-0.624) for the optimism attribute, and 0.587 (95% CI: 0.507-0.661) for the purpose attribute. Differential comparisons showed that $BERT_{Large}$ significantly outperformed Word2Vec/XGBoost in characterizing all attributes of 2 PRO domains, except for the purpose attribute in the meaning/purpose domain ($P < .05$; Table 2).

Discussion

This study employed 2 novel NLP/ML algorithms to analyze qualitative PRO data collected from pediatric cancer survivors, specifically focusing on the psychological stress and meaning/purpose domains and evaluated their performance compared to expert thematic abstraction. The findings indicate that the $BERT_{Large}$ model outperformed Word2Vec/XGBoost in both PRO domains, demonstrating higher accuracy, AUROCC, and AUPRC characterizing 3 attributes with each PRO domain.

Growing evidence in adult populations indicates that individuals with a weak sense of purpose/meaning in life face a higher risk of mortality, comparable to or even exceeding the risk of poor health behaviors such as insufficient physical activity or smoking.[11,13] Studies have also consistently shown that greater meaning/purpose in life is associated with improved daily functioning, reduced risk of chronic diseases, and lower mortality rates.[11,22,23] Although limited research exists on pediatric populations, studies indicate that meaning/purpose is linked to better academic performance, lower rates of substance use, and reduced delinquency.[16] For childhood cancer patients, the experience of cancer and its treatment is often deeply stressful, and the transition to survivorship can be associated with challenges to daily functioning, which can adversely affect their sense of meaning and purpose.[24,25] These findings highlight the importance of assessing both psychological stress and meaning/purpose for survivorship care, as they provide complementary insights to traditional clinical outcomes, potentially improving follow-up care for survivors.

The superior performance of the NLP/ML algorithms highlights the potential use of interview-based methods for assessing and interpreting qualitative PRO data on psychological stress and meaning/purpose in life, offering a valuable complement to traditional survey-based approaches for survivors. By effectively extracting meaningful information from in-depth interviews on PROs using $BERT_{Large}$ with high accuracy, clinicians can engage in deeper, more informed discussions with survivors about their psychological stress and sense of meaning/purpose. This enhanced understanding may enable the screening of patients for potential issues that could

Table 1. Performance of 2 NLP/ML models for identifying the attributes of psychological stress and meaning/purpose domains.

Domains/Attributes	NLP/ML models	Sensitivity (95% CI)	Specificity (95% CI)	Accuracy (95% CI)	AUROCC (95% CI)	AUPRC (95% CI)
Psychological stress domain						
Anger attribute	Word2vec/XGBoost	0.417 (0.279, 0.558)	0.959 (0.929, 0.985)	0.853 (0.808, 0.894)	0.878 (0.830, 0.940)	0.668 (0.560, 0.796)
	$BERT_{Large}$	0.583 (0.444, 0.725)	0.970 (0.945, 0.990)	0.894 (0.857, 0.935)	0.888 (0.820, 0.963)	0.802 (0.701, 0.886)
Controllability/manageability attribute	Word2vec/XGBoost	0.371 (0.274, 0.477)	0.821 (0.758, 0.877)	0.657 (0.592, 0.718)	0.690 (0.630, 0.789)	0.559 (0.448, 0.687)
	$BERT_{Large}$	0.584 (0.479, 0.684)	0.833 (0.771, 0.890)	0.743 (0.686, 0.796)	0.768 (0.707, 0.817)	0.696 (0.611, 0.783)
Fear/anxiety attribute	Word2vec/XGBoost	0.308 (0.200, 0.423)	0.933 (0.894, 0.967)	0.767 (0.714, 0.820)	0.787 (0.717, 0.847)	0.574 (0.442, 0.717)
	$BERT_{Large}$	0.662 (0.543, 0.769)	0.916 (0.871, 0.953)	0.848 (0.802, 0.889)	0.827 (0.757, 0.897)	0.723 (0.638, 0.848)
Meaning/purpose domain						
Goal attribute	Word2vec/XGBoost	0.280 (0.193, 0.376)	0.945 (0.923, 0.966)	0.825 (0.791, 0.854)	0.767 (0.720, 0.823)	0.416 (0.327, 0.525)
	$BERT_{Large}$	0.527 (0.430, 0.635)	0.929 (0.902, 0.951)	0.856 (0.825, 0.885)	0.848 (0.815, 0.900)	0.645 (0.553, 0.735)
Optimism attribute	Word2vec/XGBoost	0.141 (0.074, 0.217)	0.971 (0.956, 0.986)	0.823 (0.789, 0.858)	0.692 (0.629, 0.744)	0.367 (0.268, 0.472)
	$BERT_{Large}$	0.424 (0.329, 0.522)	0.955 (0.933, 0.973)	0.860 (0.830, 0.889)	0.729 (0.649, 0.797)	0.503 (0.370, 0.624)
Purpose attribute	Word2vec/XGBoost	0.348 (0.258, 0.438)	0.940 (0.917, 0.962)	0.811 (0.776, 0.844)	0.811 (0.770, 0.861)	0.533 (0.444, 0.631)
	$BERT_{Large}$	0.438 (0.348, 0.527)	0.948 (0.927, 0.968)	0.836 (0.807, 0.869)	0.800 (0.743, 0.838)	0.587 (0.507, 0.661)

Abbreviations: AUPRC = area under the precision-recall curve; AUROCC = area under the receiver operating characteristic curve; $BERT_{Large}$ = bidirectional encoder representations from transformers large model version; CI = confidence interval; ML = machine learning; NLP = natural language processing; XGBoost = eXtreme gradient boosting.

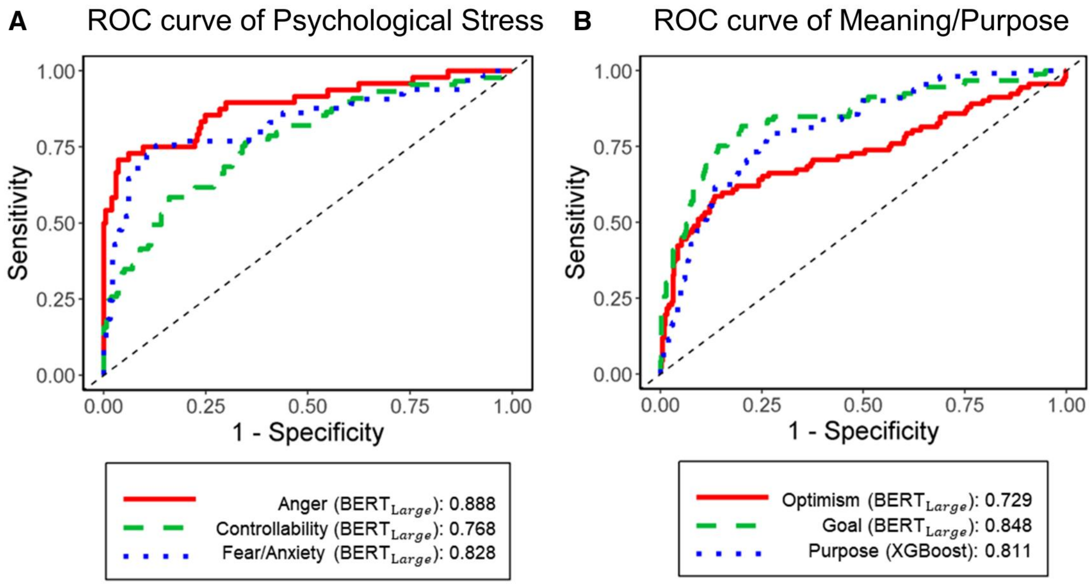

Figure 1. Area under the receiver operating characteristic curves for the best models of psychological stress domain (left column) and meaning/purpose domain (right column) by 3 attributes. (A) ROC curve of psychological stress. (B) ROC curve of meaning/purpose. BERT$_{Large}$ = bidirectional encoder representations from transformers large model version; ROC = receiver operating characteristic; XGBoost = eXtreme gradient boosting.

Table 2. Differences in area under the receiver operating characteristic curve and precision-recall curve between 2 NLP/ML models for identifying the attributes of psychological stress and meaning/purpose domains.

Domain	Attribute	AUROCC comparison between BERT$_{Large}$ and Word2vec/XGBoost Difference (95% CI)	AUPRC comparison between BERT$_{Large}$ and Word2vec/XGBoost Difference (95% CI)
Psychological stress	Anger	0.010 (−0.059, 0.076)	0.134 (0.003, 0.262)
	Controllability/manageability	0.078 (−0.003, 0.154)	0.137 (0.041, 0.228)
	Fear/anxiety	0.040 (−0.039, 0.125)	0.149 (0.003, 0.284)
Meaning/purpose	Goal	0.081 (0.025, 0.133)	0.229 (0.139, 0.308)
	Optimism	0.037 (−0.039, 0.118)	0.136 (0.020, 0.250)
	Purpose	0.015 (−0.065, 0.039)	0.054 (−0.023, 0.163)

Abbreviations: AUPRC = area under the precision-recall curve; AUROCC = area under the receiver operating characteristic curve; BERT$_{Large}$ = bidirectional encoder representations from transformers large model version; CI = confidence interval; ML = machine learning; NLP = natural language processing; XGBoost = eXtreme gradient boosting.

be addressed through targeted interventions to improve survivors' quality-of-life.[26] Furthermore, the validated NLP/ML algorithms can help extract psychological stress and meaning/purpose data directly from patients and clinical conversations, facilitating the identification of psychological stress and a reduced sense of meaning/purpose, which can inform timely and personalized care interventions.

Our successful implementation of NLP/ML suggests that this approach should be tested for its ability to identify other PRO domains (eg, pain, fatigue, depression) from semi-structured interviews, as well as from electronic health records. This approach holds significant potential for early detection of adverse events and tailoring precision medicine strategies. The interviews in this study were conducted and transcribed manually. Future research could explore automated transcription methods to enhance efficiency and reduce the cost of data collection. The application of emerging technologies could further enhance the automated coding of qualitative PRO interviews, improving efficiency, reducing data collection costs, and streamlining both research and clinical applications. Validating NLP/ML algorithms against standardized PRO surveys and established clinical benchmarks is an important area for future research to improve their reliability and facilitate integration into routine clinical practice.

Several studies have demonstrated the effectiveness of interventions in reducing psychological stress and enhancing the sense of meaning/purpose in cancer populations.[7,27] Childhood cancer survivors often report challenges such as lower academic performance, difficulties with attention or memory, and various physical and mental limitations,[28,29] which can contribute to increased stress and a diminished sense of meaning/purpose in life. Our study showed that NLP/ML can be successfully implemented to identify these needs, which could potentially be used to identify concerns and implement multidisciplinary psychosocial interventions informed by these more comprehensive assessments of psychological stress and meaning/purpose. This may help mitigate disruptions and improve long-term survivorship outcomes.

This study has several limitations. First, the sample was restricted to pediatric cancer survivors treated at one institution. While the sample included diverse diagnoses, ages, and races/ethnicities,[8] the generalizability of the findings to other populations may be limited. Second, the analysis focused on psychological stress and meaning/purpose domains, restricted

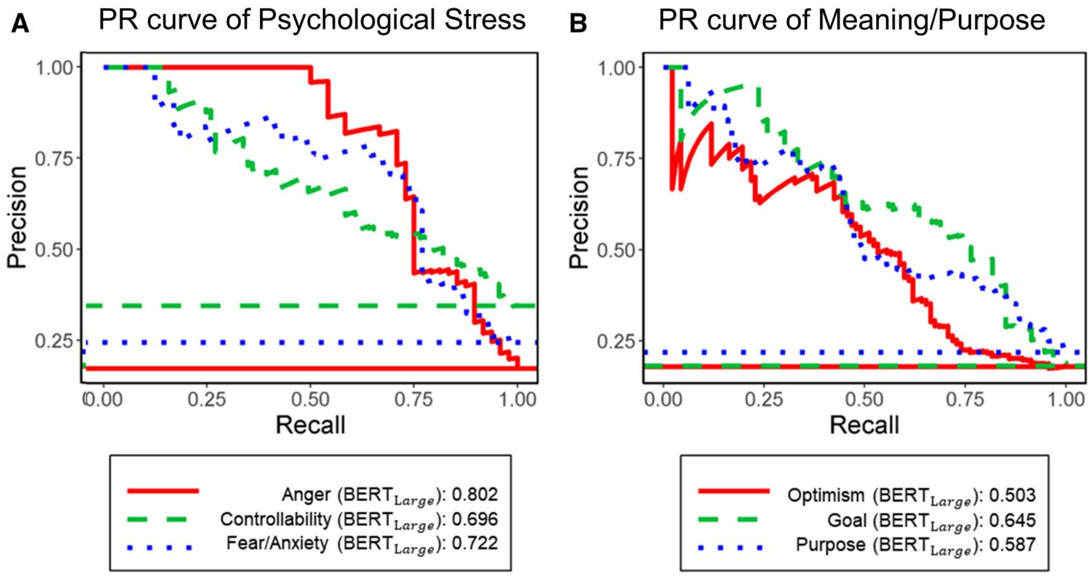

Figure 2. Area under the precision-recall curves for the best models of psychological stress domain (left column) and meaning/purpose domain (right column) by 3 attributes. (A) PR curve of psychological stress. (B) PR curve of meaning/purpose. BERT$_{Large}$ = bidirectional encoder representations from transformers large model version; PR = precision-recall.

to 6 attributes. Future research may extend the application of the BERT$_{Large}$ pipeline to other PRO domains. Third, the study employed a cross-sectional design, limiting the ability to capture temporal patterns. Validating the model using longitudinal unstructured PRO data is necessary to assess its utility in identifying time-dependent trends.

In summary, this study demonstrated the robust validity of BERT$_{Large}$ algorithms, which outperformed Word2Vec/XGBoost in characterizing psychological stress and meaning/purpose PROs for pediatric cancer survivors. Integrating NLP/ML approaches into qualitative PRO assessments, alongside other clinical data, can provide opportunities to enhance follow-up care and improve outcomes for pediatric cancer survivors.

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Author contributions

Jin-ah Sim (Investigation, Methodology), Xiaolei Huang (Formal analysis, Investigation, Methodology), Rachel T. Webster (Investigation), Kumar Srivastava (Formal analysis, Investigation), Kirsten K. Ness (Data curation, Funding acquisition, Investigation, Resources), Melissa Hudson (Funding acquisition, Investigation, Resources), Justin N. Baker (Conceptualization, Investigation, Validation), and I-Chan Huang (Conceptualization, Data curation, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation)

Supplementary material

Supplementary material is available at *JAMIA Open* online.

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Conflicts of interest

Authors have no competing interests to declare.

Data availability

The data for this article will be shared at a reasonable request by the corresponding author.

References

1. White GE, Caterini JE, McCann V, et al. The psychoneuroimmunology of stress regulation in pediatric cancer patients. *Cancers (Basel)*. 2021;13:4684.
2. Bruce M. A systematic and conceptual review of posttraumatic stress in childhood cancer survivors and their parents. *Clin Psychol Rev*. 2006;26:233-256.
3. Jones CM, Baker JN, Keesey RM, et al. Importance ratings on patient-reported outcome items for survivorship care: comparison between pediatric cancer survivors, parents, and clinicians. *Qual Life Res*. 2018;27:1877-1884.
4. Hoffman KE, McCarthy EP, Recklitis CJ, et al. Psychological distress in long-term survivors of adult-onset cancer: results from a national survey. *Arch Intern Med*. 2009;169:1274-1281.
5. Phipps S, Klosky JL, Long A, et al. Posttraumatic stress and psychological growth in children with cancer: has the traumatic impact of cancer been overestimated? *J Clin Oncol*. 2014;32:641-646.
6. Ravens-Sieberer U, Devine J, Bevans K, et al. Subjective well-being measures for children were developed within the PROMIS project: presentation of first results. *J Clin Epidemiol*. 2014;67:207-218.
7. Park CL, Pustejovsky JE, Trevino K, et al. Effects of psychosocial interventions on meaning and purpose in adults with cancer: a systematic review and meta-analysis. *Cancer*. 2019;125:2383-2393.
8. Pierzynski JA, Clegg JL, Sim JA, et al. Patient-reported outcomes in pediatric cancer survivorship: a qualitative study to elicit the

content from cancer survivors and caregivers. *BMJ Open*. 2020;10:e032414.
9. Quinto RM, De Vincenzo F, Campitiello L, et al. Meaning in life and the acceptance of cancer: a systematic review. *Int J Environ Res Public Health*. 2022;19:5547.
10. Zhao X, Tong S, Yang Y. The correlation between quality of life and positive psychological resources in cancer patients: a meta-analysis. *Front Psychol*. 2022;13:883157.
11. Alimujiang A, Wiensch A, Boss J, et al. Association between life purpose and mortality among US adults older than 50 years. *JAMA Netw Open*. 2019;2:e194270.
12. Hamer M, Chida Y, Molloy GJ. Psychological distress and cancer mortality. *J Psychosom Res*. 2009;66:255-258.
13. Hill PL, Turiano NA. Purpose in life as a predictor of mortality across adulthood. *Psychol Sci*. 2014;25:1482-1486.
14. Jim HS, Purnell JQ, Richardson SA, et al. Measuring meaning in life following cancer. *Qual Life Res*. 2006;15:1355-1371.
15. Bevans KB, Gardner W, Pajer KA, et al. Psychometric evaluation of the PROMIS® pediatric psychological and physical stress experiences measures. *J Pediatr Psychol*. 2018;43:678-692.
16. Forrest CB, Bevans KB, Filus A, et al. Assessing children's eudaimonic well-being: the PROMIS pediatric meaning and purpose item banks. *J Pediatr Psychol*. 2019;44:1074-1082.
17. Forrest CB, Forrest KD, Clegg JL, et al. Establishing the content validity of PROMIS pediatric pain interference, fatigue, sleep disturbance, and sleep-related impairment measures in children with chronic kidney disease and crohn's disease. *J Patient Rep Outcomes*. 2020;4:11.
18. Varni JW, Thissen D, Stucky BD, et al. PROMIS® parent proxy report scales for children ages 5-7 years: an item response theory analysis of differential item functioning across age groups. *Qual Life Res*. 2014;23:349-361.
19. Ye J, Yao L, Shen J, et al. Predicting mortality in critically ill patients with diabetes using machine learning and clinical notes. *BMC Med Inform Decis Mak*. 2020;20:295.
20. Du J, Chen Q, Peng Y, et al. ML-Net: multi-label classification of biomedical texts with deep neural networks. *J Am Med Inform Assoc*. 2019;26:1279-1285.
21. Kenton J-WC, Toutanova LK. BERT: pre-training of deep bidirectional transformers for language understanding. In: *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, Vol 1. Association for Computational Linguistics; 2019:4171-4186.
22. Kim ES, Shiba K, Boehm JK, et al. Sense of purpose in life and five health behaviors in older adults. *Prev Med*. 2020;139:106172.
23. Cohen R, Bavishi C, Rozanski A. Purpose in life and its relationship to all-cause mortality and cardiovascular events: a meta-analysis. *Psychosom Med*. 2016;78:122-133.
24. Winger JG, Adams RN, Mosher CE. Relations of meaning in life and sense of coherence to distress in cancer patients: a meta-analysis. *Psychooncology*. 2016;25:2-10.
25. Secinti E, Tometich DB, Johns SA, et al. The relationship between acceptance of cancer and distress: a meta-analytic review. *Clin Psychol Rev*. 2019;71:27-38.
26. Rabelais E, Jones NL, Ulrich CM, et al. Meaning making and religious engagement among survivors of childhood brain tumors and their caregivers. *Oncol Nurs Forum*. 2019;46:170-184.
27. Myrhaug HT, Mbalilaki JA, Lie NK, et al. The effects of multidisciplinary psychosocial interventions on adult cancer patients: a systematic review and meta-analysis. *Disabil Rehabil*. 2020;42:1062-1070.
28. Marcus J. Psychosocial issues in pediatric oncology. *Ochsner J*. 2012;12:211-215.
29. Zeltzer LK, Recklitis C, Buchbinder D, et al. Psychological status in childhood cancer survivors: a report from the childhood cancer survivor study. *J Clin Oncol*. 2009;27:2396-2404.

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