International Journal of Computer Science Education in Schools, March 2023, Vol. 6, No. 1
ISSN 2513-8359

Semantic Analyses of Open-Ended Responses from Professional Development Workshop Promoting Computational Thinking in Rural Schools

Amber GILLENWATERS[1]
Razib IQBAL[1]
Diana PICCOLO[1]
Tammi DAVIS[1]
Keri FRANKLIN[1]
David CORNELISON[1]
Judith MARTINEZ[1]
Andrew HOMBURG[1]
Julia COTTRELL[1]
Melissa PAGE[2]

[1]Missouri State University, Springfield, MO, United States of America
[2]The Evaluation Group, Simpsonville, SC, United States of America

DOI: 10.21585/ijcses.v6i1.136

Abstract

In this paper, an application of open-ended textual feedback is presented as a tool to evaluate the perceptions and needs of teachers tasked with implementing computational thinking in the K-12 curriculum. Semantic analysis tools, including sentiment analysis and thematic analysis, facilitated the identification of common themes in open-ended textual feedback. Results show that semantic analysis techniques can be useful in evaluating formative assessment data or open-ended feedback to discover response patterns, which may aid in determining actionable insights related to adult learner perceptions, interests, and self-efficacy. Formative assessment data were collected from a unique professional development workshop to promote computational thinking and curriculum integration in core subjects, including writing, math, science, and social studies, with the goal of discovering the barriers that rural teachers face in developing and implementing lesson plans for grades 3-8 teachers in a rural midwestern state in the USA to promote computational thinking and curriculum integration in core subjects, including writing, math, science, and social studies, with the goal of discovering the barriers that rural teachers face in developing and implementing lesson plans.

Keywords: K-12 education, rural classroom, formative assessment, teaching strategy, feedback, semantic analysis, thematic analysis, sentiment analysis

1. Introduction

According to the U.S. Bureau of Labor Statistics (2021), the demand for workers with applied knowledge in Computer Science (CS) is high and expected to continue growing at a rapid pace. However, the percentage of students participating in high school CS courses nationwide ranges from only 1-4% (Guzdial & Hill, 2019). Early access to computer education is lower among rural communities (Education Commission of the States, 2019). Teachers and students in rural areas face unique educational challenges, including high rates of poverty and unemployment (Marré, 2017). Racial and ethnic minorities from rural areas experience even higher rates of poverty and more structural barriers to pursuing CS (Wang et al., 2017) and are half as likely to obtain a college degree

(Marré, 2017). Research suggests that exposure to CS education can increase the likelihood of choosing a STEM career path by five times (Lamb et al., 2019), particularly among members of underrepresented groups (Mahadeo et al., 2020). Moreover, recent studies indicate that CS education can help students beyond computing and improve problem-solving abilities (Brown & Brown, 2020; Salehi et al., 2020).

Therefore, K-12 educators, especially in rural areas, need to play a synergistic role in preparing students adequately for CS professions. According to a recent report published by Code Advocacy Coalition (2021), many states have established K-12 CS performance standards. However, K-12 CS programs across the United States vary widely in terms of content and programming tools and languages offered (Hubwieser et al., 2015). In addition, teaching resources and standardized knowledge assessments are still in development. Chetty et al. (2014) indicated that there are shortages of qualified teachers who understand the concept of computational thinking. Therefore, offering CS education to all students in K-12 school systems remains a challenging goal due to a lack of teacher education training in the areas of computational thinking and software development skills. Although professional development (PD) workshops with the goal of providing K-12 teachers with appropriate computer science training across the USA are gaining traction (Code Advocacy Coalition, 2021), there are factors present that impede the implementation of computing knowledge and related activities in the course activities. As computer science professional development in K-12 is relatively new, the literature suggests that the aggregation of open-ended responses can be particularly useful when an area is understudied (Clarke & Braun, 2014), which motivated us to develop a streamlined approach to analyze the open-ended feedback from the teacher PD workshops. The aim was to provide evidence for the following research questions:

> *RQ1*: Are the semantic analysis techniques a suitable and practical approach to evaluating open-ended feedback from teachers participating in computer science professional development?
>
> *RQ2*: What are some motivations, barriers, and areas of concern present in this group of rural teachers?

The goal of this paper is to apply the semantic analysis techniques to the feedback provided by a population of rural teachers participating in professional development as they implement and develop computer science educational material in their classrooms. The semantic analysis approach is intended to reveal the impact of the experience of rural teachers participating in a PD workshop in applied computational thinking to demonstrate the efficacy of these proposed techniques.

2. Textual Data Analysis

Given the overall lack of teachers knowledgeable in CS, PD initiatives have been taken to engage teachers in computing workshops to familiarize them with CS concepts and block-based programming skills (Liu et al. 2011). As K-12 teaching programs are pioneered throughout the United States, data collection and high-quality data analysis throughout the development process are essential to ensure teachers' needs are met to the greatest extent possible. As noted by Clarke and Braun (2014), qualitative semantic analysis of open-ended responses is particularly useful when a topic area is not well-specified in theory or the setting requires a contextualist approach, both of which are applicable in this case, as the optimal instructional methods to prepare grade 3-8 teachers to integrate CS concepts and computational thinking in the core curriculum is not well-studied or clearly defined.

2.1 Formative Assessment

A variety of formative assessments were used to collect feedback from teachers each day during the workshop resulting in a wide range of open text responses. Formative assessments are open-ended prompts that are used to monitor learning. This feedback can be used to determine the level of understanding and confidence in the material and to help identify appropriate corrective adjustments in instruction (Guskey, 2005). Evidence suggests these strategies encourage self-reflection in learning (Black & Wiliam, 2009), increase engagement (Benotti et al., 2017), and are associated with higher scores on summative knowledge assessments (Hashemi, et al., 2016). The formative assessment prompts used in the analysis were strategies supported with moderate to strong evidence in the Institute of Education Sciences What Works Clearinghouse Practice Guide called Teaching Secondary

Students to Write Effectively (Graham et al., 2016). Formative assessment strategies included K-W-L-S (Ogle, 1986; Steele & Dyer, 2014), 3-2-1 (Djudin, 2021), Exit Card Reflection (Patka, et al., 2016), and Plus/Deltas (Helminski, 1995). In brief, K-W-L-S ask learners to describe what they know, want to know, learned, and still want to know. The 3-2-1 is an informational and persuasive prompt in which learners are asked to write three things they learned, two things they would like to learn more about, and one question they have on the topic. Exit card reflections requested details on ideas gained, insights relating to participation, suggestions for improvement, and questions. Plus/deltas prompted thoughts on positive aspects and suggested changes. See Appendix for full item text. Teachers received a presurvey prior to the workshop and submitted their suggestions/feedback online at the end of each day as part of the workshop's activities.

2.2 Semantic Analysis

Semantic analysis refers to the general study of the syntax of open-text data to derive meaning. Qualitative data analysis is useful in determining similarities and contiguity in textual data, as per Maxwell and Chmiel (2014). Increasingly, semantic analysis is being applied as a promising means to assess learners throughout the learning process. For instance, Masood et. al (2022) describe a series of preprocessing steps used to evaluate informal student feedback followed by sentiment analysis. Another recent application evaluated the sentiment of students impacted by isolation during quarantine as instruction was changed unexpectedly to an online format for a long period of time (Pastor, 2020). Chen, Li, & Huang (2020) tested an approach based on word segmentation and word clusters to provide output instantly associated with online discussions. Gottipati, Shankararaman, and Lin propose a series of preprocessing and analysis steps to automate qualitative text from end-of-course feedback (2018). In this case, thematic analysis and sentiment analysis were applied.

2.2.1 Thematic Analysis

Thematic analysis is a form of qualitative semantic analysis technique where a set of procedures is applied to either induce or deduce common themes from qualitative data to identify patterns of response (Clarke & Braun, 2014). Thematic analysis helps provide flexibility in handling complex data, particularly when the interpretation of semantic meaning may vary widely while maximizing adequate data representation, especially when outcomes are not easily predicted (Nowell et al., 2017). In this case, classifying responses using thematic analysis was expected to provide information on teacher perceptions vital to optimal instruction by the workshop team. For instance, it is possible that teachers may question the benefit of spending valuable classroom time teaching computational thinking. In that case, it would be wise to provide evidence and a rationale to the teachers on the advantages for their students. On the other hand, if teachers understand the benefits and are eager to learn more, spending more workshop time on applied computing skills would be appropriate.

Thematic analysis can be accomplished with either an inductive or deductive approach. Inductive methods of thematic analysis incorporate semantic clustering allowing themes to emerge. An inductive method is helpful in cases where unexpected patterns of response may appear (Nowell, et al., 2017). For example, this can help extract the major topics or themes that teachers most often describe in their responses to the prompts. Deductive methods of classification derive themes based on prior expectations or theory. The most appropriate deductive schema for the classification of open-ended questions that elicited expressions of concern based on the context and types of response was the Concern-Based Adoption Model (CBAM) from Newlove and Hall (1976). CBAM is a well-established framework for classifying open-ended statements of concern from teachers tasked with implementing a new program in their schools. Chamblee and Slough (2004) provide a comprehensive meta-analysis using CBAM in technology implementation. Gabby et al. used CBAM to gather feedback from chemistry teachers introducing technical content (2017). The coding model is paraphrased from the original in Table 1.

Table 1. Concerns-based adoption model classification

Label	Primary Concern Expressed in Statement
Awareness	Little concern or involvement is indicated.
Informational	Substantiative aspects in a selfless manner such as general characteristics/requirements.
Personal	Uncertainty relating to demands, personal role, and personal adequacy.
Management	Processes and tasks involve the best use of information and resources.
Consequence	Relevance for students, e.g., student outcomes and performance and competency evaluation.

Collaboration	Coordination and cooperation with others regarding use.
Refocusing	Universal benefits. Individual has definite ideas about alternatives to proposed or existing form.

Classifications are paraphrased from "A manual for assessing open-ended statements of concern about an innovation" by Newlove and Hall (1976).

2.2.2 Sentiment Analysis

Sentiment analysis refers to the methodological comparison of widely available tools to determine the polarity of emotional valence, generally either a positive or negative affect and sometimes including a measure of intensity associated with individual words, statements, or sets of statements (Feldman, 2013). Sentiment analysis can help identify statements where words associated with positive feelings or negative feelings are included. The advantage of sentiment analysis is to identify indications of strong emotions within answers. Expressions with a negative rating may indicate high emotionality and stress relating to the learning experience, something the workshop leaders would want to acknowledge and help with as soon as possible. It can also help identify strong motivators and reasons for excitement during the learning process.

3. Method

3.1 Research Setting

Motivated by initiatives like Liu et al. (2011) and the other challenges mentioned above, a multi-year project was initiated to provide instruction and support for grade 3-8 teachers in a rural midwestern state to implement computational thinking as a problem-solving framework in their daily instruction. A week-long PD workshop was launched in the Summer of 2021 with support from a federal grant. This program is an interdisciplinary effort developed and led by a diverse group of eight university professors representing multiple departments, fields of study, and backgrounds. The project aimed to incorporate writing in introducing CS while aligning with state performance standards in English, Math, Science, Social Studies, and CS. The workshop aimed to develop teachers' content knowledge and efficacy in integrating CS with STEAM (science, technology, engineering, arts, and math), project-based learning in Alice and Scratch (grade-level appropriate programming tools) and using Raspberry Pi in their current curriculum. The teachers were compensated for their participation in this workshop and have committed to continuing the project throughout the year in exchange for further compensation for their time and support from a federal grant program.

3.2 Participant Characteristics

In order to best support schools serving high-needs students, participants in the first-year teacher launch workshop consisted of twenty-nine teachers recruited from schools in a rural midwestern state with a Small Rural School Achievement (SRSA) and/or a Rural Low-Income Schools (RLIS) designation also carrying a Title I designation. Although information on race was not collected, the sample was predominantly white. The presurvey included 33 participants, whereas the actual participants in the workshop included 23 females and 6 males. The midwestern U.S. state from which the sample originated has been characterized as having moderate levels of rural poverty and a primarily agricultural property tax base, according to Showalter, et al. (2017). Inductive thematic analysis showed that the group represented a broad range of years of experience teaching (Figure 1), and their level of education varied (Figure 2).

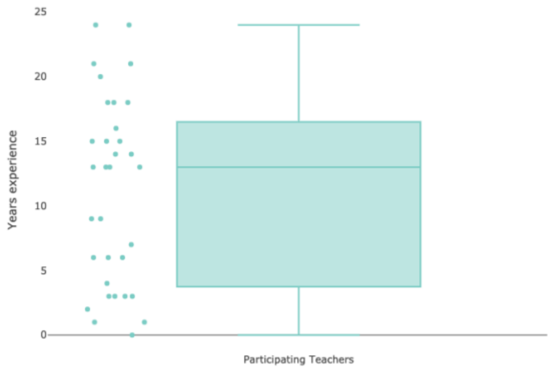

Figure 1. Years Experience

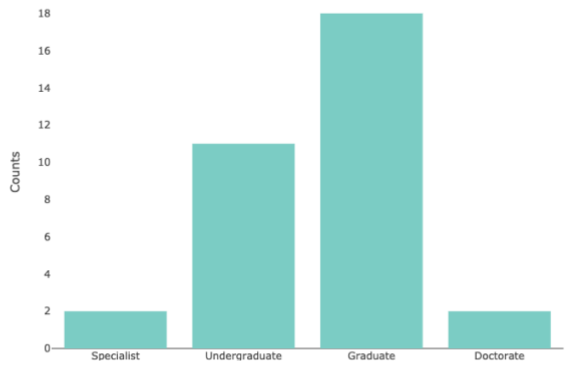

Figure 2. Level of Education

3.3 Thematic Analysis

Open-text feedback was collected before, during, and immediately after the workshop in response to multiple types of formative assessments, including K-W-L-S, 3-2-1, exit card, and plus/delta. To prepare the data for analysis, the following steps were taken. After spellchecking, a basic tokenization process was applied, splitting each textual response into individual alphanumeric units using standardized parsing and using regular expressions [\string^[:alnum:][:space:]’’]. Next, a list of standard English stop words from NLTK was used to identify and label stop words. For the frequency charts only, know, want, learn, and the numbers 3, 2, and 1, were added to the stop word list since these terms were within prompts and appeared often in the replies, and then the stop word list was excluded. This resulted in a word set of 5,041 tokens. In addition, simple plurals were changed manually to the same token as the singular form, e.g., “computer” and “computers” were changed to “computer(s)”, and proper nouns such as “Raspberry” and “Pi” were considered single term “Raspberry Pi” for aggregation. Inductive coding for some statements was determined using researcher triangulation; that is, responses were clustered into groups by two independent raters. These items related to the level of education (Specialist, Undergraduate, Graduate, or Doctorate), years of experience, and experience coding, which was open-text to allow for flexible self-report, as well as prompts requesting general comments or suggestions. For deductive analysis, two independent raters interpreted and applied CBAM classification to all open-ended responses with a third rater to resolve ties. Some items appeared to elicit statements involving concern more than others, such as what teachers learned, hoped to learn, and what unique needs their students had. A selection of several of these items is summarized in the results. For sentiment analysis, the preprocessing steps above were applied. This resulted in a word set of 9,961 words.

3.4 Sentiment Analysis

Sentiment analysis was derived using two tools, the SocialSent Programming domain-based lexicon from Hamilton, et al. (2016) and NLTK VADER (Natural Language Took Kit Valence Aware Dictionary for Sentiment Reasoning, Bird, 2006). These tools are well-established, free, and readily available online. Both tools incorporate word embedding which refers to the likelihood of positive or negative sentiment based on the co-occurrence of neighboring words, after training on large corpora to provide context-specific results. SocialSent was derived from the top 250 Reddit forum subcommunities in 2014, while VADER was trained on historical Twitter data. All lexicons considered were tested for suitability with an inner join, matching terms from the test set and each lexicon. The match ratio is the number of words from the open-response data that were also present in the lexicon after stop word removal. The SocialSent 2014 Programming lexicon was selected as it demonstrated a high word match ratio (82%) after stop word removal. NRC (Mohammad & Turney, 2013), Bing (Hu & Liu, 2004), AFINN (Nielsen, 2011), Loughran & Mcdonald, 2011) were excluded prior to analysis because the word match ratio was 15% or lower.

VADER’s polarity score function results in a compound score that has undergone normalization, with each statement being assigned a number ranging from -1 representing a negative polarity and +1 indicating a positive expression. A value close to zero indicates relative neutrality. The VADER tool is capable of handling various pitfalls in textual analysis, such as negation or more informal speech, by considering the semantic meaning of the piece of text in full (Bird, 2006). For example, the statement beginning with “If I'm being really honest here, the first thing that stood out to me was how much passion, excitement, and connectedness there already was. . .” resulted in a compound sentiment score of 0.99. Whereas a negative statement that began with “It is frustrating that we can't necessarily use Alice with our students if we don't have hard drives. . . “resulted in a compound sentiment score of -0.68. An example of an emotionally laden word from the SocialSent lexicon present in open-ended responses included “great” with a mean sentiment rating value assignment of 4.26, whereas “slow” had a mean sentiment value assignment of -3.12. For comparison with NLTK VADER, a summative score was calculated, adding the scores of the words by the response. Using more than one tool allowed for comparison and for some degree of cross-validation.

4. Results

In this section, a selection of outcomes is described after the use of inductive and deductive thematic analysis and a comparison of sentiment analysis with the SocialSent programming lexicon and NLTK VADER results applied to the open-ended questions from the workshop (see Appendix).

4.1 Inductive Thematic Analysis

Inductive thematic analysis was used to summarize participant characteristics, including the number of years of teaching experience (Figure 1) and level of education (as seen in Figure 1 and Figure 2), to determine participant classroom needs from open-text data. In response to "How much have you coded?", almost all (93%, N = 29) respondents reported either having not coded at all (n = 17) or described feeling like a beginner with only a superficial understanding of block-coding and computer concepts (n = 6). Two reported teaching CS classes and felt somewhat confident. This form of inductive coding worked particularly well for suggestions and comments. For instance, responses to "What can we do to make tomorrow better?" included requests for certain foods or drinks (n = 5), environmental preferences (e.g., room temperature, n = 4), and accessibility improvements (n = 4), such as the number of breaks, pacing, and improving visibility. Otherwise, this item was left blank (n = 6) or complemented the experience overall, using the terms "good" or "great" n = 11). Keeping communication open and making sure learners are as comfortable as possible was important for the research team and seemed to improve the experience of the workshop participants. Upon review of token frequencies in this group, there was high word commonality within the K-W-L-S (Figure 3) and 3-2-1 strategies (Figure 4). Summarizing responses in this manner is helpful in determining topic areas that stood out the most for learners and in seeing common themes at a glance. This allowed the team to review the growth in the same participants as learning progressed. It is expected that over time responses will likely become more unique as the teachers begin to understand and feel more comfortable with the field of computer science.

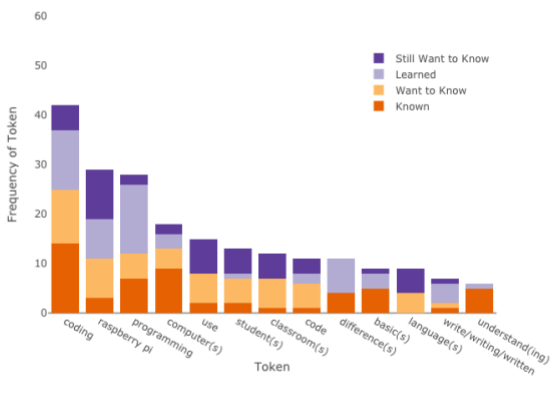

Figure 3. K-W-L-S Token Count

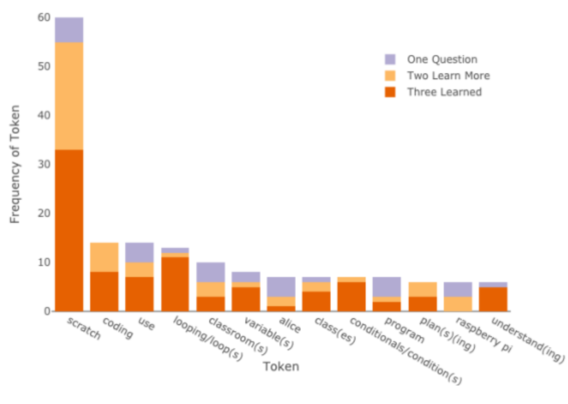

Figure 4. 3-2-1 Token Count

4.2 Deductive Thematic Analysis

In Figure 5, CBAM analysis is presented as applied to the open-ended responses given during the workshop, with criteria summarized in Table 1. This analysis demonstrated that teachers are highly motivated by meeting the needs of their students, as represented by the category of response labeled "Consequence". When asked what they hoped to learn during the week, teachers overwhelmingly expressed wanting to learn to better serve their students, e.g., "I am hoping to get more ideas to get kids excited to code and use logical reasoning!" When asked "How we can best support you as a learner. . ." , responses were often self-reflective, and tended to incorporate a sense of self-doubt in their efficacy in learning and applying CS content, as represented by the category labeled "Personal". Examples of these statements were as follows: "I will need lots of patience and hands-on experience" and "Lots of grace, coding is not my strong suit, but I will do my best". The "Unconcerned" category was applied to responses like "None at this time". On Day 1 of the workshop, "Informational" concerns were higher, where the focus is primarily on details and facts. For instance, on the want-to-know item, one teacher said, "What is Raspberry Pi capable of". On Day 3, more teachers were concerned with "Consequences", that is, relevance for their students and classrooms, e.g., "I want to know how Scratch is used with core content." and "Personal" responses describing the content in relation to themselves.

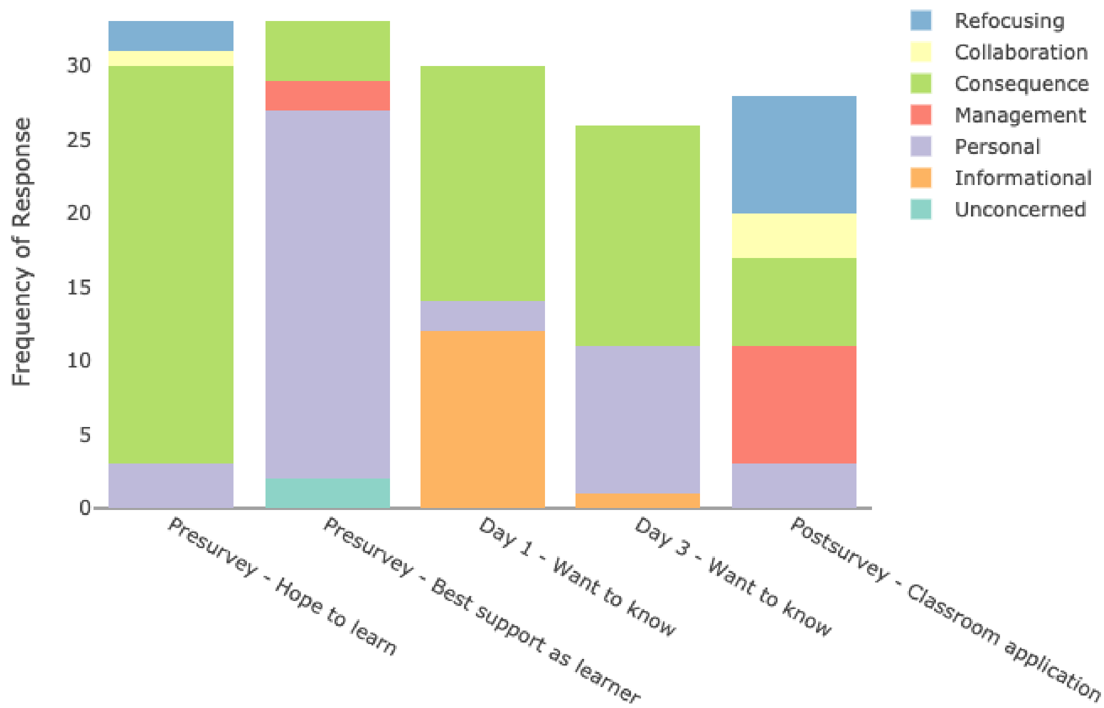

Figure 5. CBAM Deductive Analysis

4.3 Sentiment Analysis

A histogram of output was reviewed to check for normality across all individual statement scores, as seen in Figure 6. The SocialSent lexicon demonstrated a normal distribution, while the NLTK VADER result was leptokurtic, with most statements classified as close to neutral in tone. While NLTK VADER was generally in agreement with more extreme scores, results from SocialSent are summarized here. SocialSent results were evaluated using summary scores by prompt, as demonstrated in Figure 7. Teachers used words with highly positive emotional valence most often in answering what they hoped to learn. Responses to Plus +, or what they felt was working, were also high. Delta, which requested feedback on opportunities for improvement in presented content, was the lowest scoring item. Relatively low scorers also included thoughts on classroom applications and the unique needs of their students. SocialSent appeared useful for evaluating expressions on an individual response level basis as well. Both tools (CBAM and VADER) appeared to help identify areas of strength and specific problems to be addressed.

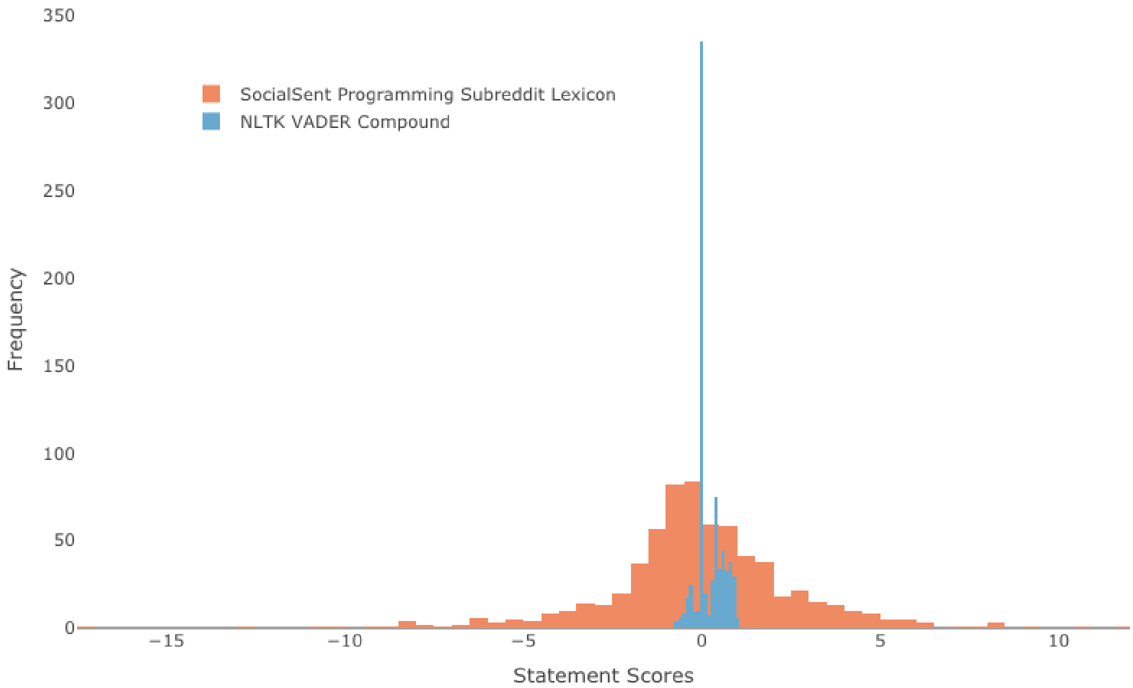

Figure 6. Comparison of SocialSent with NLTK

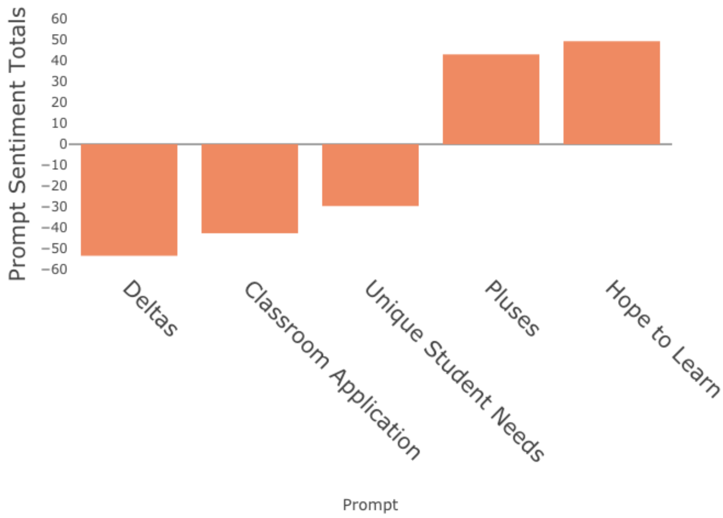

Figure 7. SocialSent Items with High Emotionality

5. Discussion and Conclusion

In this paper, various methods of semantic analysis are presented to evaluate the utility and practicality of handling open-ended textual responses from teachers in PD workshops. These methods included lexicon-based and word-embedded sentiment analysis, using both inductive and deductive approaches to derive patterns representing the learning experience of the participants. This approach is novel as a practical implementation suitable for regular use in that the study design utilizes open-source and readily available tools, an important factor since time and resources are often strained in a classroom setting. While open-response prompts are common, the volume of data can quickly become difficult to manage and more prone to subjectivity without the use of proper data analysis techniques. There is no existing standardized or streamlined process to make use of this form of valuable data.

Inductive methods of thematic analysis served to allow workshop organizers to intervene and correct issues that might otherwise decrease the likelihood of teacher success. For example, during the workshop, the team became aware that a sufficient number of computer monitors with HDMI capability were not available in some schools to be used with Raspberry Pi, and Alice was not usable on the only device available, Google Chromebooks. Collecting and aggregating open-response data from participants with these types of issues allowed the team to make adjustments and follow up to assist with resource management which would otherwise pose a serious barrier to successful implementation. Deductive methods using CBAM analysis provide information on areas of concern and level of comfort with material for teachers incorporating a new curriculum. In this case, participating teachers represented a wide range of comfort levels, with some describing feeling eager to move forward as fast as possible, while others felt the presentation was at the right pace. Therefore, self-paced activities and paired programming seemed helpful in meeting group needs.

CBAM proved to be an effective diagnostic tool to determine barriers that participating teachers face in classroom implementation to help the team to adjust the presentation and content of materials in the workshop and beyond. For example, on the first day of data collection, almost all teachers expressed fear and self-doubt. Whereas, by the last day of data collection, about one-third of the participants communicated excitement and described specific ways in which they plan to incorporate the material learned into their class, labeled "Refocusing". An example of a Refocusing statement is "Help my science students create models to represent what they are learning or problem-solve scenarios through [S]cratch". A few teachers expressed interest in collaborating with others in their schools which was classified as "Collaboration". An example of a Collaboration statement is "I already teach coding but would def [definitely] love to collaborate with other teachers and bring some of their hands-on projects alive with coding". A number of individuals discussed time management and process as well, which was classified under

"Management": "My main goal is to start by integrating coding into a core subject one day per week. I hope to increase this as I feel comfortable".

In this group, CBAM was effective in assessing changes in confidence over time. CBAM revealed that initially, self-doubt among teachers was prevalent. Providing high support and sufficient time to practice appeared to be an effective intervention until confidence began to increase. When confidence in the form of interest in collaboration and/or refocusing ideas was high, the teachers expressed readiness to learn more conceptual information and maintain high levels of engagement. CBAM may help inform more specific lines of follow-up questioning in the future in the target group.

The outcomes of sentiment analysis using SocialSent suggest that using words with strong emotionality in either direction of polarity may be associated with learners being overwhelmed or being ready to learn more. An example of a low-scoring response was "Shorter breaks and more frequent. Think breaks, so much information in a short time. Almost overloading." Another participant listed several specific frustrations relating to a lack of hardware at their school and expressed the feeling this was overlooked by the team. Unique needs included "High poverty, lack of access at home and lack of experience" or mention of large class sizes. A positive high-scoring statement was "Great introduction to Coding. Very positive experience. Well-organized and planned. Love how there are different presenters" or "I am just excited to bring a new program full of possibilities to my students". Sentiment analysis is useful to target learners expressing high emotionality and can assist PD facilitators to implement timely interventions among learners with the most need of support.

There are some limitations to the interpretation based on the nature of this study. The generalizability of these methods depends on the data used and the context. The small sample size may influence how representative these data are of rural teachers from the target group. In sentiment analysis, generally, questions relating to the unknown tended to be more negative in tone. However, this skew may be partially due to associations from the Reddit programming sub-community from which the lexicon was derived that may not reflect the true feelings of the teachers. For example, the word "teacher" has a particularly low score in the SocialSent programming lexicon, but teachers using the word "teacher" are not likely to share that negative connotation. While teachers were extremely hard-working and enthusiastic throughout the week, mental fatigue after an intensive workshop with a daily commute may have influenced their responses. In addition, the SocialSent lexicon was highly applicable in this particular use case but may be somewhat dated since the set was derived from a 2014 forum. Language relating to computing and user attitudes are apt to change over time as technology progresses. Finally, the attitudes expressed may be transitory in nature or influenced by the wording in the questions themselves. More research is needed to confirm any apparent trends within the findings reported here and to follow up appropriately as the team supports the teachers in the process of curriculum integration during the academic year.

This paper aimed to demonstrate whether semantic analysis is a practical approach to finding common themes among participants in a PD workshop. It was anticipated that this could act as a diagnostic tool for teams to gain information helpful to organize teacher PD workshops, identify resources needed in their school settings, as well as potential areas of improvement. Overall, the textual analysis of open-ended formative assessments showed promise to quickly identify common themes and identify learners needing a challenge or support. Therefore, the methodology described can be used to effectively analyze open-ended responses from participants in similar PD initiatives, without which the organizers may fail to address barriers teachers face in successfully implementing the workshop objectives.

Acknowledgments

Research reported was supported by a $4 million grant from the Early-Phase Education, Innovation and Research (EIR) Program of the U.S. Department of Education (USDE) under award number S411C200085. The content is solely the responsibility of the authors and does not necessarily represent the official views of the funding agency.

References

Benotti, L., Martinez, M. C., & Schapachnik, F. (2017). A tool for introducing computer science with automatic formative assessment. *IEEE Transactions on Learning Technologies*, *11*(2), 179-192. Retrieved from https://doi.org/10.1109/TLT.2017.2682084

Bird, S. (2006, July). NLTK: The natural language toolkit. In *Proceedings of the COLING/ACL 2006 Interactive Presentation Sessions* (pp. 69-72). Retrieved from https://aclanthology.org/P06-4018.pdf

Black, P., & Wiliam, D. (2009). Developing the theory of formative assessment. *Educational Assessment, Evaluation and Accountability (formerly: Journal of Personnel Evaluation in Education), 21*(1), 5–31. Retrieved from https://doi.org/10.1007/s11092-008-9068-5

Brown, E., & Brown, R. (2020). The Effect of Advanced Placement Computer Science Course Taking on College Enrollment. *West Coast Analytics*. Retrieved from https://www.cuny.edu/wp-content/uploads/sites/4/page-assets/about/administration/offices/oira/policy/seminars/APHighSchoolManuscript_JHRNotypset.pdf

Chamblee, G., & Slough, S. (2004). Using the concerns-based adoption model to assess changes in technology implementation. In *Society for Information Technology & Teacher Education International Conference* (pp. 864-871). Association for the Advancement of Computing in Education (AACE). Retrieved from https://www.learntechlib.org/primary/p/13584/

Chen, C. M., Li, M. C., & Huang, Y. L. (2020). Developing an instant semantic analysis and feedback system to facilitate learning performance of online discussion. *Interactive Learning Environments*, 1-19. Retrieved from https://doi.org/10.1080/10494820.2020.1839505

Chetty, R., Friedman, J. N., & Rockoff, J. E. (2014). Measuring the impacts of teachers II: Teacher value-added and student outcomes in adulthood. *American Economic Review, 104*(9), 2633–79. Retrieved from https://doi.org/10.1257/aer.104.9.2633

Clarke, V., & Braun, V. (2014). Thematic analysis. In *Encyclopedia of Critical Psychology* (pp. 1947–1952). Springer, New York, NY. Retrieved from https://doi.org/10.1007/978-1-4614-5583-7_311

Code Advocacy Coalition (2021). State of computer science education: Accelerating action through advocacy. Retrieved from https://advocacy.code.org/2021_state_of_cs.pdf

Djudin, T. (2021). Promoting students' conceptual change by integrating the 3-2-1 reading technique with refutation text in the physics learning of buoyancy. *Journal of Turkish Science Education, 18*(2), 290–303. Retrieved from http://www.tused.org/index.php/tused/article/view/734/668

Education Commission of the States (2019). Stem content: Give more united states students early access to computer science. Retrieved from https://vitalsigns.ecs.org/state/united-states/curriculumprogram-grade-stats

Feldman, R. (2013). Techniques and applications for sentiment analysis. *Communications of the ACM*, *56*(4), 82-89. Retrieved from https://doi.org/10.1145/2436256.2436274

Gabby, S., Avargil, S., Herscovitz, O., & Dori, Y. J. (2017). The case of middle and high school chemistry teachers implementing technology: Using the concerns-based adoption model to assess change processes. *Chemistry Education Research and Practice*, *18*(1), 214-232. Retrieved from https://www.learntechlib.org/primary/p/13584/

Gottipati, S., Shankararaman, V., & Lin, J. R. (2018). Text analytics approach to extract course improvement suggestions from students' feedback. *Research and Practice in Technology Enhanced Learning*, *13*(1), 1-19. Retrieved from https://doi.org/10.1186/s41039-018-0073-0

Graham, S., Bruch, J., Fitzgerald, J., Friedrich, L. D., Furgeson, J., Greene, K., ... & Smither Wulsin, C. (2016). Teaching Secondary Students to Write Effectively. Educator's Practice Guide. What Works Clearinghouse.™ NCEE 2017-4002. *What Works Clearinghouse*.

Guskey, T. R. (2005). Formative Classroom Assessment and Benjamin S. Bloom: Theory, Research, and Implications [Paper presentation]. *Annual Meeting of the American Educational Research Association*, Montreal, Canada. Retrieved from https://files.eric.ed.gov/fulltext/ED490412.pdf

Guzdial, M., & Hill, R. K. (2019). Getting high school, college students interested in CS. *Communications of the ACM, 62*(12), 10–11. Retrieved from https://doi.org/10.1145/3365581

Hamilton, W. L., Clark, K., Leskovec, J., & Jurafsky, D. (2016, November). Inducing domain-specific sentiment lexicons from unlabeled corpora. In *Proceedings of the Conference on Empirical methods in Natural Language Processing*. NIH Public Access. Retrieved from https://doi.org/10.18653/v1/D16-1057

Hashemi, A., Mobini, F., & Karimkhanlooie, G. (2016). The impact of content-based pre-reading activities on iranian high school EFL learners' reading comprehension. *Journal of Language Teaching and Research, 7*(1), 137. Retrieved from https://doi.org/10.17507/jltr.0701.15

Helminski, L. (1995). Total quality in instruction: A systems approach. In H. V. Roberts (Ed.), Academic initiatives in total quality for higher education (pp. 309–362). Milwaukee, WI: ASQC Quality Press.

Hu, M., & Liu, B. (2004, August). Mining and summarizing customer reviews. In *Proceedings of the Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 168-177). Retrieved from https://doi.org/10.1145/1014052.1014073

Hubwieser, P., Giannakos, M. N., Berges, M., Brinda, T., Diethelm, I., Magenheim, J., ... & Jasute, E. (2015). A global snapshot of computer science education in K-12 schools. In *Proceedings of the 2015 ITiCSE on Working Group Reports* (pp. 65-83). Retrieved from https://doi.org/10.1145/2858796.2858799

Lamb, R., Annetta, L., Vallett, D., Firestone, J., Schmitter-Edgecombe, M., Walker, H., ... Hoston, D. (2018). Psychosocial factors impacting STEM career selection. *The Journal of Educational Research, 111*(4), 446–458. Retrieved from https://doi.org/10.1080/00220671.2017.1295359

Liu, J., Lin, C. H., Hasson, E. P., & Barnett, Z. D. (2011, March). Introducing computer science to K-12 through a summer computing workshop for teachers. In *Proceedings of the 42nd ACM technical symposium on computer science education* (pp. 389-394). Retrieved from https://doi.org/10.1145/1953163.1953277

Loughran, T., & McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance, 66*(1), 35-65. Retrieved from https://doi.org/10.1111/j.1540-6261.2010.01625.x

Mahadeo, J., Hazari, Z., & Potvin, G. (2020). Developing a computing identity framework: Understanding computer science and information technology career choice. *ACM Transactions on Computing Education (TOCE), 20*(1), 1–14. Retrieved from https://doi.org/10.1145/3365571

Marré, A. (2017). Rural education at a glance, 2017 edition. *U.S. Department of Agriculture, Economic Research Service, Economic Information Bulletin, 171*. Retrieved from https://www.ers.usda.gov/webdocs/publications/83078/eib-171.pdf?v=3841.6

Masood, K., Khan, M. A., Saeed, U., Al Ghamdi, M. A., Asif, M., & Arfan, M. (2022). Semantic Analysis to Identify Students' Feedback. *The Computer Journal, 65*(4), 918-925. Retrieved from https://doi.org/10.1093/comjnl/bxaa130

Maxwell, J. A., & Chmiel, M. (2014). Notes toward a theory of qualitative data analysis. *The SAGE Handbook of Qualitative Data Analysis*, 21-34.

Mohammad, S. M., & Turney, P. D. (2013). Crowdsourcing a word-emotion association lexicon. C*omputational Intelligence*, *29*(3), 436-465. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-8640.2012.00460.x

Newlove, B. W., & Hall, G. E. (1976). A Manual for Assessing Open-Ended Statements of Concern About an Innovation. Retrieved from https://eric.ed.gov/?id=ED144207

Nielsen, F. Å. (2011, March). AFINN: A new word list for sentiment analysis on Twitter. *Informatics and Mathematical Modelling*, Technical University of Denmark. Retrieved from http://www2.compute.dtu.dk/pubdb/pubs/6010-full.html

Nowell, L. S., Norris, J. M., White, D. E., & Moules, N. J. (2017). Thematic analysis: Striving to meet the trustworthiness criteria. *International Journal of Qualitative Methods*, *16*(1). Retrieved from https://doi.org/10.1177/1609406917733847

Ogle, D. M. (1986). K-W-L: A Teaching Model That Develops Active Reading of Expository Text. *The ReadingTeacher*, *39*(6), 564–570. http://www.jstor.org/stable/20199156

Patka, M., Wallin-Ruschman, J., Wallace, T., & Robbins, C. (2016). Exit cards: creating a dialogue for continuous evaluation. *Teaching in Higher Education*, *21*(6), 659–668. Retrieved from https://doi.org/10.1080/13562517.2016.1167033

Salehi, S., Wang, K. D., Toorawa, R., & Wieman, C. (2020, February). Can majoring in computer science improve general problem-solving skills? In *Proceedings of the 51st ACM Technical Symposium on Computer Science Education* (pp. 156–161). Retrieved from https://doi.org/10.1145/3328778.3366808

Showalter, D., Klein, R., Johnson, J., & Hartman, S. L. (2017). Why Rural Matters 2015-2016: Understanding the Changing Landscape. A Report of the Rural School and Community Trust. *Rural School and Community Trust*. Retrieved from https://files.eric.ed.gov/fulltext/ED590169.pdf

Steele, J., & Dyer, T. (2014). Use of KWLS in the online classroom as it correlates to increased participation. *Journal of Instructional Research*, *3*, 8–14. Retrieved from https://files.eric.ed.gov/fulltext/EJ1127637.pdf

U.S. Bureau of Labor Statistics (2021, May). Occupational Outlook Handbook: Computer and information technology occupations. Retrieved from https://www.bls.gov/ooh/computer-and-information-technology/home.htm

Wang, J., & Hejazi Moghadam, S. (2017, March). Diversity barriers in K-12 computer science education: Structural and social. In *Proceedings of the 2017 ACM SIGCSE Technical Symposium on Computer Science Education* (pp. 615-620). Retrieved from https://doi.org/10.1145/3017680.3017734

Appendix

Items Used in Analysis	***Semantic Analysis***
Presurvey	
What is your highest level of education?	Researcher Triangulated (Fig. 1)
Including this school year, how many years have you been employed as a teacher?	Researcher Triangulated (Fig. 2)
What do you hope to learn by participating in the CODERS project? (Hope to learn)	CBAM (Fig 5.), Sentiment Analysis (Fig. 6, Fig. 7)
How can we best support you as a learner during the CODERS summer workshop? (Best support as learner)	CBAM (Fig 5.), Sentiment Analysis (Fig. 6, Fig. 7)
How much have you coded?	Researcher Triangulated (Sec. 4.1)
Day 1 (K-W-L-S)	
K - What I know or think I know (Known)	Token Frequency (Fig. 3), CBAM
W - What I want to know (Want to know)	Token Frequency (Fig. 3), CBAM (Fig.5)
L - What I learned (Learned)	Token Frequency (Fig. 3), CBAM
S - What I still want to know (Still want to know)	Token Frequency (Fig. 3), CBAM
What do we need to know to make tomorrow better?	Researcher Triangulated (Sec. 4.1)
Day 2 (Pluses/Deltas +/∆ ***)***	
Identify things that are working (Pluses +)	Researcher Triangulated, Sentiment Analysis (Fig. 6, Fig. 7)
Identify opportunities for improvement (Deltas ∆)	Researcher Triangulated, Sentiment Analysis (Fig. 6, Fig. 7)
Day 3 (3-2-1)	
What are three things you learned? (Three Learned)	Token Frequency (Fig. 4), CBAM, Sentiment Analysis (Fig. 6)
What are two things you want to learn more about? (Two Learn More/Day 3 - Want to know)	Token Frequency (Fig. 4), CBAM, Sentiment Analysis (Fig. 6)
What's one question you have? One Question	Token Frequency (Fig. 4), CBAM, Sentiment Analysis (Fig. 6)
Day 4 (Exit Card) As a result of my participation, here are:	
Ideas I have gained	CBAM, Sentiment Analysis (Fig. 6)
Insights I have about what helped me learn, process, and/or fully participate	CBAM, Sentiment Analysis (Fig. 6)
Suggestions I have for how to make the work stronger	Researcher Triangulated, Sentiment Analysis (Fig. 6)
Questions I have	Researcher Triangulated, Sentiment Analysis (Fig. 6)
Postsurvey	
Describe your thoughts about applying computational thinking and programming skills using Alice and/or Scratch in your classroom (Classroom application)	CBAM, Sentiment Analysis (Fig. 6, Fig. 7)
What unique needs do your students have that you think CODERS needs to know about? (Unique student needs)	CBAM, Sentiment Analysis (Fig. 6, Fig. 7)
What suggestions do you have to improve the teacher launch in the future?	CBAM, Sentiment Analysis (Fig. 6)