

## What “Neutral” Really Means in Online Conversations about Student Debt?

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### Objective and Significance

Student loans are a growing concern for many individuals for both their time in university and post-graduation. With student loan debt now crossing \$1.8 trillion (Hanson, 2026), this financial obligation has become a defining factor in shaping career choices, continued education, family planning, homeownership, and overall financial stability (Ulbrich & Kirk, 2017; Zhan & Sinha, 2019). Beyond these economic impacts, recent research has begun to explore the psychological and emotional consequences of student loan debt. The weight of student loan debt persists well beyond college, contributing to ongoing financial anxiety and stress throughout adulthood (Lindgren et al., 2023). Yet, the sentiments and emotions are often difficult to capture through traditional research methods such as surveys or interviews, which may not reflect how debt-related stress is expressed in real-time (Sinha et al., 2023, 2024).

Despite the growing recognition of financial anxiety and debt-related stress, the current gap in mental health services leaves many borrowers without adequate support (Pabayao et al., 2022). High treatment costs, limited access to providers, and persistent stigma around seeking help prevent individuals from addressing the emotional toll of debt through traditional care (Lindgren et al., 2023). As a result, borrowers often manage these struggles on their own, turning instead to informal outlets such as online communities (Lawson et al., 2023). Examining how people express their emotions in these online spaces offers an opportunity to better understand the unmet needs associated with student loans.

Rapid advancements in natural language processing (or NLP) provide new opportunities to study how consumers communicate emotions related to a variety of issues in authentic settings. Social media platforms such as Reddit are particularly becoming important in this regard, as they host candid conversations where consumers discuss their personal struggles, including those tied to debt and financial insecurity. These platforms provide researchers with a rich and real-time source of data for understanding consumer experiences more deeply.

However, detecting emotions in such online discourse remains challenging. Posts are often informal and filled with slang or context-specific language, which complicates automated analysis. Additionally, NLP classification models frequently categorize a high proportion of posts as “neutral,” suggesting that subtle emotional cues may be overlooked. Our study seeks to fill this gap. We applied transformer-based models and keyword extraction techniques to re-examine posts initially classified as neutral. Our purpose was twofold: First is to evaluate how transformer-based models capture emotions in overrepresented posts classified as neutral. Second, we seek to refine the neutral classification and analyze the linguistic patterns of posts through keyword extraction methods to uncover hidden emotional dimensions that traditional approaches may overlook.

### Methodology

For this study, we obtained users’ posts from Reddit, as this platform has many unique features. Unlike platforms such as Twitter, Reddit allows users to remain anonymous and engage in longer discussions, which is important when it comes to topics of personal finance and debt. The community-like structure of this platform allows users to both seek and offer advice to one another, creating a space where a wide range of emotions related to student loan debt, such as stress, frustration, regret, or hope, can be openly expressed. A total of 225,355 posts were collected between 2008 and 2020, just around the US government student loan pause due to COVID-19. We first analyzed data using the RoBERTA-base-go\_emotions model from Hugging Face to identify specific emotions. This pre-existing model has been trained on different Reddit data and can identify 28 distinct emotions. Since this model is familiar

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with Reddit language, it understood the language within the data set and was able to recognize many different emotions, including admiration, fear, confusion, curiosity, and more.

However, a large proportion of posts were flagged as “neutral,” which piqued our curiosity to explore the emotions further. To do this, we filtered the dataset to only include neutral posts, reducing the dataset to 67,794 posts. We then preprocessed this data to eliminate any numbers and kept responses shorter than 15-20 words from the ‘Contents’ column on the dataset. Next, we used the Emotion English DistilRoBERTa-base model and obtained a new dataset of the top\_emotion, as well as a spread of scores for 7 specific emotions: anger, disgust, fear, joy, neutral, sadness, and surprise that add up to 1 for each Reddit post. This helped us with a more detailed analysis of the emotions expressed in each post, as well as with grouping. Using these results, we grouped the responses based on their respective proportion of neutral. The groups were: 0-.25, .25-.5, .5-.75, and .75-1, and labeled them groups 1 through 4 correspondingly.

Finally, we identified specific characteristics of these posts and compiled a list of key question words to better understand the kinds of questions users were asking, as well as to refine the evaluation of neutral posts into more specific emotions. To achieve this, we ran the text classification model: KeyBERT, an open-source keyword extraction technique that implements BERT embeddings to find keywords that are most similar to the given dataset, the text classification model Bag-of-Words, and finally the TF-IDF model. Through the use of these three models, we had a more extensive comparison of what the most common words were picked up within the proportions of each neutral group.

### Results

The results showed distinct themes across each of the three models. For the first group, KeyBERT identified keywords related to 401(k) borrowing and lending, while Bag-of-Words and TF-IDF emphasized financial repayment terms such as *car*, *pay*, *month*, *money*, and *credit*. In the second group, the dominant themes focused on credit and payment concerns, with KeyBERT identifying terms such as *debts tuition* and *college loaning*, while Bag-of-Words and TF-IDF highlighted words including *credit*, *pay*, *month*, and *card*. The third group contained more advice-oriented and discussion surrounding affordability, with KeyBERT capturing phrases such as *tuition advice*, *budget advice*, and *struggling affordable*, while the other models again populated repayment-related terms like *pay*, *month*, *credit*, and *year*. Finally, the fourth group focused more on language surrounding repayment and financial management strategies. In this group, KeyBERT identified terms such as *tuition deduction* and *deducting tuition*, while Bag-of-Words and TF-IDF found words such as *plan*, *pay*, *income*, *credit*, and *repayment*. The combination of these three models within each subgroup demonstrates that although these posts were classified as neutral, they still contain underlying emotions such as financial stress, repayment concerns, and advice-seeking behavior.

### Conclusion and Relevance

In recent years, the US government has attempted bold measures to address the student debt crisis, including a one-time loan forgiveness plan that proposed canceling up to \$20,000 for eligible borrowers. At the same time, the rising costs of higher education continue to drive future generations into debt, making one-time relief programs neither sustainable nor sufficient. Understanding how borrowers experience and communicate the ongoing burden of student loan debt is therefore increasingly important.

Online communities provide one space where borrowers publicly discuss their struggles, share their uncertainties, seek advice, and express their stress associated with student loans. Using data from an online community on Reddit, our study demonstrates that posts previously classified as “neutral” still contain meaningful emotional signals, especially around financial stress and advice-seeking behavior.

The persistence of these conversations across several years reinforces prior findings that student loan debt is associated with enduring psychological distress, anxiety, and financial strain (Dwyer, 2018; Walsemann et al., 2019). By applying our refined emotion detection and keyword extraction models, we were able to uncover hidden expressions of anxiety related to student loan repayment, 401(k) borrowing, and debt management. Our study has three key implications. First, improving the accuracy of emotion detection models contributes to the development of more reliable NLP tools that can be applied to a wide range of social and behavioral research contexts. Second, uncovering the hidden dimensions of financial anxiety and debt stress provides insights into the everyday struggles of borrowers, many of whom remain underserved by traditional mental health systems. Finally, our findings highlight the potential of social

media as a resource for monitoring public well-being, particularly for policymakers, educators, and mental health professionals to better address the emotional consequences of student loan debt.

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