Exploring the Effect of Federal Student Loan Payment Resumption on Borrowers Through Sentiment and Textual Analysis Using X

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Abstract

Student loans have taken on an increasingly significant role in funding the higher education experience and payments toward student loan debt have become an important part of many borrowers' overall financial plan. Using Brandwatch, this study analyzes X data to better understand student loan borrower sentiment during the resumption of federal student loan payments in October 2023. During the period studied, negative references to student loans on the platform overtook positive sentiment overwhelmingly (46% negative versus 1% positive). Topics and phrases labeled negative sentiment ranked higher in mentions than those with positive or neutral sentiment in their respective categories. The findings highlight the need for financial planners to provide appropriate mental health resources to help borrowers manage negative feelings surrounding the federal student loan payment restart.

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Introduction

Given the increasing costs of college education, many college attendees rely on student loans to complete their degrees. According to the National Center for Education Statistics (2023), the average total cost for a first-time, full-time undergraduate student living on campus at a public 4-year institution during the 2021-2022 academic year was $26,000. For first-time, full-time undergraduate students attending private nonprofit 4-year institutions, the price tag was much higher at $55,800.

From March 13, 2020, to September 1, 2023, the U.S. Department of Education paused payments and set interest rates to 0% on eligible federal student loans as part of the nation's COVID-19

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Disclosure: We employed AI algorithms, specifically Brandwatch, to analyze the data collected for this study. The AI methods were selected based on their suitability for the research objectives and data characteristics.

emergency relief measures. During this same period, the Biden Administration proposed a plan to forgive up to $20,000 for qualifying borrowers. This plan was ultimately blocked by the U.S. Supreme Court in June 2023. After this decision, student loan interest was set to begin accruing in September 2023 with payment resumption in October 2023.

The breakneck pace of student loan changes over the last four years has undoubtedly affected student loan borrowers, who must now address their student loan debt in addition to cumulative societal transitions brought on by the pandemic. This project seeks to understand student loan borrower sentiment during payment resumption through an analysis of their expressions on social media. An increased understanding of borrower sentiment will help financial professionals better appreciate the mental health ramifications of this financial transition on borrowers.

The authors wish to make a point of clarification in light of company name changes that could create confusion for the reader. In July 2023, Elon Musk rebranded the well-known microblogging platform, Twitter, to X. Because this change is so recent, however, most previous studies will refer to the platform by its former name, Twitter. To avoid confusion, the authors have chosen to refer to the platform as X in this paper, even retroactively, unless Twitter is referenced directly in a quote or article title.

The purpose of this research is to evaluate the emotional impact of recent student loan changes on borrowers. One way to gauge the emotional change within student loan borrowers is through the proxy of textual sentiment during times of major student loan changes. To proxy student loan borrowers, researchers can measure individuals who discuss student loans on X. As mentioned previously, from early 2020 to late 2023 student loan borrowers made no payments or accrued interest on eligible federal student loans, and the Biden Administration proposed a generous loan forgiveness program. After the denial of student loan forgiveness, interest accrual resumed in September 2023 and payments in October 2023. This paper seeks to address the following question: How did sentiment change on X during the resumption of federal student loan payments in October 2023? Based on the findings of Sinha et al. (2023) – which are covered later in the literature review - we hypothesize that:

H_1: Negative sentiment will outweigh positive sentiment during the study's date range.

H_2: Topics and phrases with negative sentiment will rank higher in mentions than those with positive or neutral sentiment during the study's date range.

Literature Review

Student Loans

Because student loans are readily accessible to students, generally have lower interest rates than private loans, and offer fixed rates, it is no surprise that their usage has increased (Ebrahimian, 2023). Despite their popularity, borrowers have polarized views about student loans. As a means of funding their education, some borrowers feel that the cost is worth it, while others feel weighed down (Nuckols et al., 2020). Such feelings often prompt individuals to share their student debt experiences on social media platforms.

Student loans have been shown to have numerous effects on borrowers. For example, Kim and Chatterjee (2019) identified a negative association between student loans and an individual's life satisfaction and psychological well-being. Student loans have also been associated with psychological distress, financial anxiety, and other negative forms of health and psychological well-being (Archuleta et al., 2013; Kim & Chatterjee, 2019; Zhang et al., 2019). Student loans have also had negative outcomes to the extent that some individuals develop problems with mental health, smoking, and heavy drinking (Qian et al., 2021).

Not all borrowers view student debt the same way. Borrowers in the repayment period of their loans reported higher psychological distress than those who were still enrolled in a university (Sato et al., 2020). In addition, and when compared to individuals without student loans, those repaying their loans had lower levels of financial satisfaction (Kim et al., 2021). Reflecting contradictory findings, Joseph and MacDonald

(2021) concluded that student loans are negatively associated with financial satisfaction, while Robb et al. (2018) found no significant effect. The contradicting results from these studies highlight the complexity of the relationship between student loans and the emotional state of borrowers.

In addition to the psychological effects associated with student loan debt, asset accumulation has also been highlighted in research. Mountain et al. (2020) found that student loans negatively affected Millennials' homeownership rates. Also of concern, student debt has been associated with a reduced likelihood to save for retirement (Elliott et al., 2013). Beyond concerns related to retirement and housing, student loan borrowers are more likely to carry other types of debts, like car and credit card debt (Fry, 2012).

Debt repayment reduces disposable income for borrowers, and the resulting lack of liquidity can make it more challenging to finance other purchases (Gicheva & Thompson, 2014). Furthermore, having student debt hinders borrowers' ability to spend. In a recent paper, 18% of student loan holders reported difficulty buying daily necessities because of their existing debt (Hanson, 2023).

Social Media as a Data Source

In contrast to traditional research sources, social media data is "user-generated, naturalistic, and unstructured," creating a fascinating opportunity for researchers to explore public opinion on a variety of topics (Sinha et al., 2023, p. 736). Social media as a tool to express opinions has become more popular as the number of users has increased with the availability of the internet (Ortiz-Ospina, 2019). While social media may be used to share various types of information, it has also been used to express sentiment on specific topics that affect a wide range of individuals.

Considering its massive growth, companies and media organizations are interested in exploring X user data as a means of detecting user sentiment on various products and services (Kouloumpis et al., 2011). Likewise, significant interest has developed among researchers for purposes of better understanding the public's opinion on important topics. What makes X (and social media in general) advantageous from a research standpoint is that it provides insight into the minds of users by the voluntary posting of their thoughts, expressions, as well as their interactions with other platform users in "a naturalistic setting" (De Choudhury et al., 2013, p. 128) and in real-time (Edo-Osagie et al., 2020).

Chancellor et al. (2020) note that new computational methods of social media data analysis could make significant differences, such as using social media data to identify and provide interventions for risky behavior. The significant number of users also provides a benefit to researchers in that there are a large sample of tweets to look at. As Zimbra et al. (2018, p. 24) notes, "Many researchers and firms have recognized that valuable insights on issues related to business and society may be achieved by analyzing the opinions expressed in the abundance of tweets".

The Use of Social Media Data in Research

Harvesting social media data is a non-traditional means of obtaining the opinions and sentiment of subjects. Traditional forms of gathering opinion and sentiment data include the use of surveys to try to determine how study participants feel about a particular issue. The internet and modern technologies have created new spaces for researchers to gather data (Edo-Osagie et al., 2020). In their research seeking to identify depression on X, Nadeem et al. (2016) found that social media data represents a potential solution to problems that can arise in self-reported depression questionnaires in that postings on social media often provide a window directly into the state of mind of the social media user. Researchers can use social media data to "automatically identify self-expressions" in the construction of a given data set (Coppersmith et al. 2014, p. 52).

Limited research has been conducted to date using social media and X for analysis of student loans. One notable exception is a 2023 study by Sinha et al. looking at student loans and mental health expressions on Reddit and X. Sinha et al. (2023) used Scarcity Theory to explore Reddit and X data to improve understanding of the relationship between student loans and mental health. They found that social media posts about student loans were associated with negative sentiment and had a higher likelihood of containing expressions of sadness and fear.

A large body of work used X and other social media data to study mental illness and mood disorders. In their review of studies attempting to predict mental illness, Guntuku et al. categorized studies into two camps: finding correlates to, or identifying, mental illness (2017, p. 43). Preoţiuc-Pietro et al.'s (2015) research focused on predicting "linguistic markers" of mental illness (p. 28) while De Choudhury et al. (2013) predicted major depression using X. Similarly, Chancellor et al. (2020) used social media data to identify mood and psychosocial disorders. Reece et al. (2017, p. 8) used X to predict depression and PTSD, noting that their "method identified these mental health conditions earlier and more accurately than the performance of trained health professionals, and was more precise than previous computational approaches". Finally, Coppersmith et al. (2018) demonstrated how automatic procedures using social media data and Natural Language Processing (NLP) can detect suicide risk.

Considering the unique way individuals use social media, researchers are naturally attracted to it as a means of examining a variety of behaviors, moods, opinions, and sentiment. Because X allows users to express themselves and interact with others, researchers can monitor sentiment and analyze data with relative ease. Social science explores the interaction of individuals in their environments with other human beings, and X documents these interactions in a way that can be informative to the social science researcher. In their research, *Quantifying Mental Health Signals in Twitter*, Coppersmith et al. noted that "social media is by nature *social*, which means that social patterns, a critical part of mental health and illness, may be readily observable in raw Twitter data." (2014, p. 51).

Coppersmith et al. (2014) successfully used X data to perform individual and population-level analyses to identify mental health disorder signals for depression, bipolar disorder, post-traumatic stress disorder, and seasonal affective disorder. In another study, Coppersmith et al. were able to "easily and automatically" identify X users with PTSD by "scanning for tweets expressing explicit diagnoses" instead of relying on "traditional PTSD diagnostic tools" (2014, p. 579). Tsugawa et al. (2015, p. 9) found that by analyzing X user history data that "depression can be recognized in users with an accuracy of approximately 69%".

While text is typically the object of analysis for researchers, Guntuku et al. looked at image postings and profile pictures on X for clues relating to user mental health and found that anxious users tended to post more photos, and both depressed as well as anxious users posted images "dominated by grayscale" (2019, p. 244). Edo-Osagie et al. (2020) undertook a scoping review of the use of X for public health research and found that studies most often used X data for surveillance, event detection, pharmacovigilance, forecasting, disease tracking, and geographic identification.

Sentiment Analysis

The vastness of social media calls for useful summarization tools to gain insights into the underlying data. Sentiment analysis can automate this otherwise cumbersome process to pull opinionated data from massive datasets (Giachanou et al., 2017). Sentiment analysis strives to improve the automatic recognition of sentiment within a text (Zimbra et al., 2018) and detects opinions based on features selected by researchers (Giachanou et al., 2017).

While there are a variety of ways to seek to understand student loan sentiment among borrowers, sentiment analysis offers a unique opportunity. As noted previously, automating the processing of large chunks of data is valuable from an efficiency and effectiveness standpoint. Most beneficial, in the opinion of the authors, is the opportunity to understand borrower sentiment as expressed by them without prompting from a researcher. In a way, sentiment analysis allows researchers to observe human behavior in its natural habitat.

X Sentiment Analysis

X is a microblogging platform that allows users to publish their opinions on virtually any topic. Social science researchers can examine user sentiment with relative ease on a wide range of issues and across a large population considering X's substantial user base and significant number of daily messages (Giachanou et al., 2017). X sentiment analysis may be viewed as a "specialized area within sentiment analysis" (Zimbra et al., 2018, p. 3) where X data is mined for opinionated text on a given topic (Giachanou et al., 2017), with sentiment detection occurring through the establishment of word embeddings (Carvalho et al., 2021).

X sentiment analysis is not without its challenges. Some of these challenges include length limitation of messages (Giachanou et al., 2017), "novel language" resulting from length of message constraints (Zimbra et al., 2018, p. 24), as well as written errors and content that is constantly changing (Giachanou et al., 2017). Despite its challenges, X sentiment analysis remains an important tool for researchers. It offers direct insights from users, shedding light on public opinions on critical issues (Giachanou et al., 2017).

Methodology

On June 23, 2023, X removed academic API access and significantly lowered the caps allowed for data collection by academics. This development made it nearly impossible for academics to gather data in a cost-effective manner for use in open-sourced statistical software or readily available data science models. In light of these challenges during the creation of this study, the author team elected to use Brandwatch (https://www.brandwatch.com/) to collect social media data. Using this software, data was collected containing the term "student loan" and the hashtag #studentloans from October 1 to October 31, 2023 (the query was exported on November 1, 2023). The query was set to collect all mentions of student loans across various content sources, including X, Reddit, Tumbler, YouTube, news sites, blogs, forums, and review sites. Instead of collecting all data across these platforms, Brandwatch collected a statistically significant sample size with a calculated rate of 33.36%. The export filtered out pornographic content and profanities. This larger dataset (n = 317,394 with 208,595 unique authors) was filtered to collect only records from X (n = 248,303 with 176,640 unique authors), which represented 78.2% of the comprehensive dataset. The final sample for this study was 248,303.

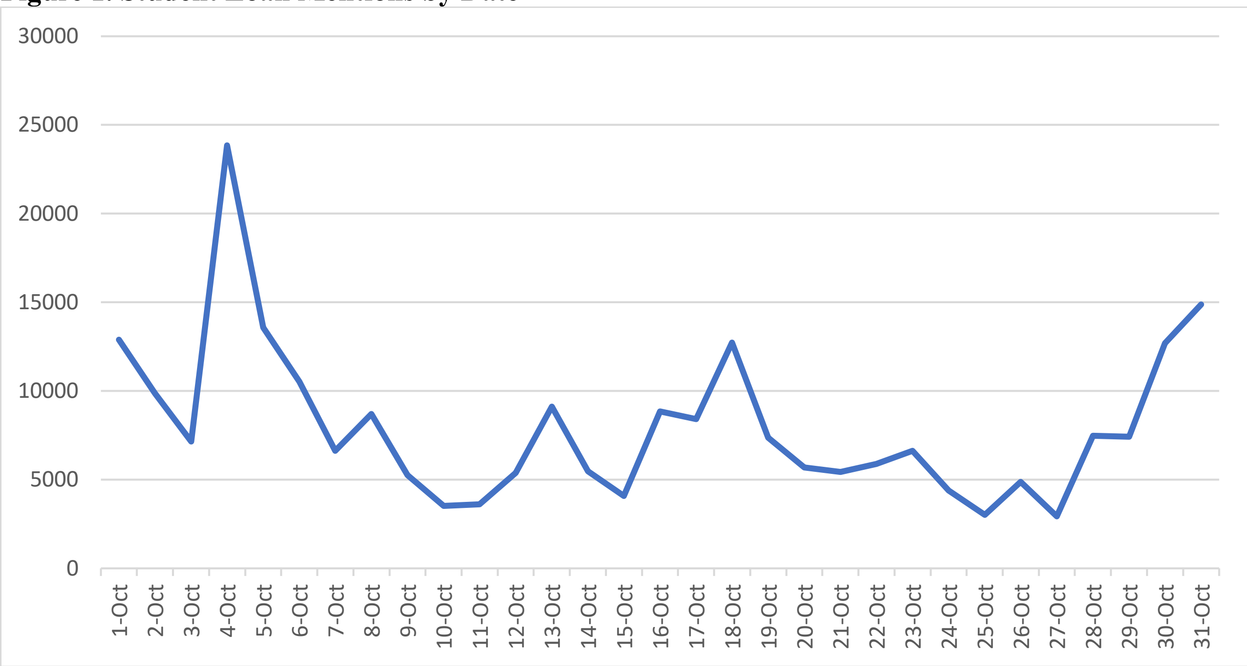
A textual and sentiment analysis of the collected data was conducted within the Brandwatch online software. Brandwatch defines sentiment analysis as "the process used to determine the attitude, opinion and emotion expressed by a person about a particular topic in an online mention" (Brandwatch, 2023). A sentiment score is calculated based on the proximity of sentiment and search terms, within the context of larger blocks of text (Brandwatch, 2023). Importantly, if a collection of text cannot be accurately categorized as positive or negative, it is classified as neutral (Brandwatch, 2023).

Brandwatch conducts sentiment analysis and calculates sentiment scores using proprietary algorithms, machine learning, and Natural Language Processing ("NLP") (Brandwatch, 2023). Specifically, Brandwatch uses a pre-trained model using transformer-based deep learning technology to assign sentiment scores (Brandwatch, n.d.-a; Brandwatch, n.d.-b). Transformer models are commonly used to analyze sentiment for social media data and have been used to analyze data from X (Bokolo & Liu, 2024; Gong et al., 2022; Kokab et al., 2022; Padmalal et al., 2024; Sharma et al., 2022). The sentiment model was trained on user annotated sentiment material from the Brandwatch platform, third party datasets from academic studies, annotation service data, and Brandwatch in-house data (Brandwatch, n.d.-a). Sentiment accuracy across languages is estimated to be between 60-75% with an average F1 predictive performance of 55-65% (Brandwatch, n.d.-a). This accuracy range reflects the challenge of conducting a sentiment analysis across a large dataset, specifically, the tradeoff inherent in a data science model between accuracy and bias (Brandwatch, n.d.-a). Brandwatch's model has been benchmarked to others such as MonkeyLearn, Aylien, Idol, Metamind, AlchemyAPI, and Datumbox with comparable performance (Brandwatch, n.d.-a).

Results

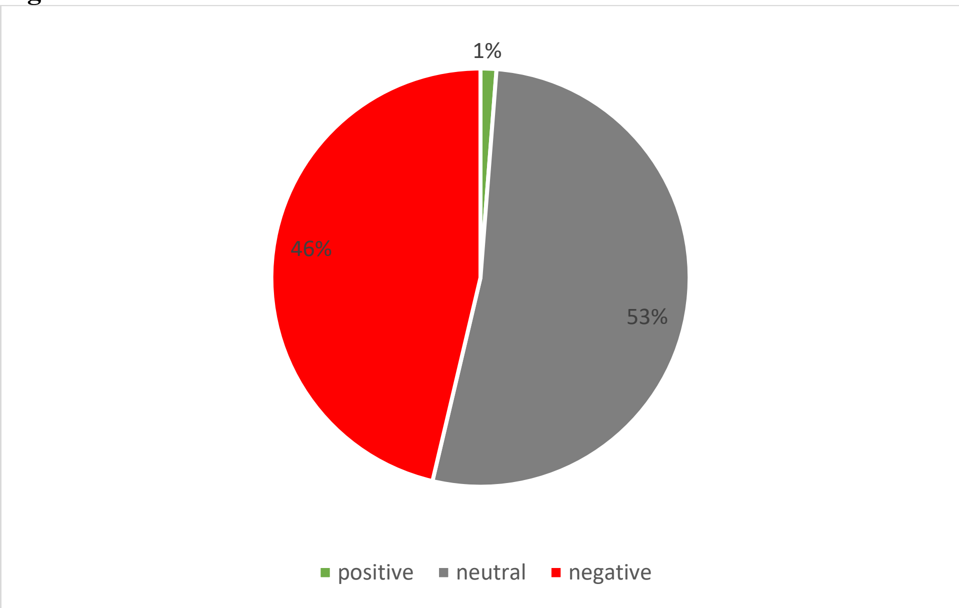
Figure 1 shows the number of mentions per day across the date range. The mean was 8,009 and the median 7,147. Between September 30 and October 23, mentions spiked on four days: October 1 (n = 12,888), October 4 (n = 23,849), October 18 (n = 12,732), and October 31 (n = 14,882). Figure 2 Provides the overall sentiment for student loan mentions within the study's data range. Most of the mentions were neutral (53%), with 46% negative and 1% positive. This finding supports the first hypothesis, as negative sentiment overwhelmingly outweighs positive sentiment during the date range.

Figure 1. Student Loan Mentions by Date



Note: n = 248,291. Brandwatch excluded twelve records when completing this analysis.

Figure 2. Overall Sentiment for Student Loan Mentions



Note: n = 248,301. Brandwatch excluded two records when completing this analysis.

Table 1 provides additional detail on the twenty most popular phrases, persons, and keywords with sentiments of neutral, negative, and positive along with the category sentiment score. The top-ranking keyword was *debt*, with 106,605 mentions, followed by *forgiveness* (42,010), *billion* (32,453), *tax* (30,804), and *money* (27,854). The top-ranking person – in fact, the only person listed in the top twenty topics – was *Biden* (45,422), who also ranked as the second most popular topic across types (*President* is also listed as twentieth on this list with 17,805 mentions). The top-ranking topics for negative sentiment were *debt* (69,286 negative sentiment versus 722 positive sentiment), *money* (24,742 negative sentiment versus 104 positive sentiment), *tax* (22,976 negative sentiment versus 38 positive sentiment), *Biden* (20,935 negative sentiment versus 218 positive sentiment), and *genocide* (20,539 negative sentiment versus 26 positive sentiment). Every topic, keyword, and phrase listed in the top twenty most popular topics had a negative sentiment score, supporting our second hypothesis.

To further investigate the findings presented in Table 1 and provide contextual meaning, a positive to negative sentiment ratio was created. This ratio was then compared to the number of mentions. The correlation between the positive-negative sentiment ratio and mentions was calculated to be 0.149, indicating a weak, positive relationship. This weak relationship further supports the findings and gives context to any potential bias in interpretation of high frequency words. When Table 1 was sorted by highest positive-negative sentiment ratio, the top five results form a cluster around student loans: borrowers (0.028), forgiveness (0.026), student loan payments (0.023), payments (0.020), and President (0.015). However, each of these ratios remains quite low at <0.03.

Table 2 groups each of the top topics into three broad categories (student loans, government, and other/ambiguous) to better focus on borrower sentiment attached to student loans. The average positive-negative sentiment ratio was calculated for each category. The student loans category had the highest average positive-negative sentiment ratio at 0.021. The next highest categories were government (0.005) and other/ambiguous (0.002).

Table 1. Top 20 Topics by Mentions and Corresponding Sentiment Statistics

Topic Name	Type	Mentions	Negative	Neutral	Positive	Sentiment Score	+/- Ratio
debt	Keyword	106605	69286	36596	722	-64	0.010
Biden	Person	45422	20935	24268	218	-45	0.010
forgiveness	Keyword	42010	16435	25150	425	-38	0.026
billion	Keyword	32453	14024	18377	50	-43	0.004
tax	Keyword	30804	22976	7788	38	-74	0.002
money	Keyword	27854	24742	3006	104	-88	0.004
payments	Keyword	24643	10852	13571	218	-43	0.020
relief	Keyword	22649	15013	7488	146	-65	0.010
women	Keyword	20785	17928	2851	5	-86	0.000
genocide	Keyword	20638	20539	71	26	-99	0.001
Americans	Keyword	20536	9218	11248	68	-44	0.007
borrowers	Keyword	19924	7300	12420	203	-35	0.028
student loan payments	Phrase	19906	8613	11095	197	-42	0.023
tax money	Phrase	19834	19756	77	0	-99	0.000
children	Keyword	19762	18614	1124	23	-94	0.001
voted	Keyword	18593	6397	12165	29	-34	0.005
hard	Keyword	18557	18029	515	11	-97	0.001
universal	Keyword	18200	17697	494	8	-97	0.000
health care	Phrase	17883	17754	119	8	-99	0.000
President	Keyword	17805	5840	11875	89	-32	0.015

Table 2. Average Topic Positive-Negative Sentiment Ratio Across Categories

Topic Name	Type	Mentions	Negative	Neutral	Positive	Sentiment Score	+/- Ratio
Category: Student Loans							
debt	Keyword	106605	69286	36596	722	-64	0.010
forgiveness	Keyword	42010	16435	25150	425	-38	0.026
payments	Keyword	24643	10852	13571	218	-43	0.020
borrowers	Keyword	19924	7300	12420	203	-35	0.028
student loan payments	Phrase	19906	8613	11095	197	-42	0.023
						Average +/- Score	**0.021**
Category: Government							
Biden	Person	45422	20935	24268	218	-45	0.010
tax	Keyword	30804	22976	7788	38	-74	0.002
money	Keyword	27854	24742	3006	104	-88	0.004
Americans	Keyword	20536	9218	11248	68	-44	0.007
tax money	Phrase	19834	19756	77	0	-99	0.000
voted	Keyword	18593	6397	12165	29	-34	0.005
health care	Phrase	17883	17754	119	8	-99	0.000
President	Keyword	17805	5840	11875	89	-32	0.015
						Average +/- Score	**0.005**
Category: Other/Ambiguous							
billion	Keyword	32453	14024	18377	50	-43	0.004
relief	Keyword	22649	15013	7488	146	-65	0.010
women	Keyword	20785	17928	2851	5	-86	0.000
genocide	Keyword	20638	20539	71	26	-99	0.001
children	Keyword	19762	18614	1124	23	-94	0.001
hard	Keyword	18557	18029	515	11	-97	0.001
universal	Keyword	18200	17697	494	8	-97	0.000
						Average +/- Score	**0.002**

Table 3 displays the twenty most popular phrases with sentiments of neutral, negative, and positive, along with the category sentiment score. The top-ranking phrases were *student loan payments* (19,906 mentions), followed by *tax money* (19,834), *health care* (17,883), *forgiving student loan debt* (17,469), and *funding a genocide* (17,217). Regarding the mix of sentiment, 16/20 (80%) of topics had a negative sentiment score, and 4/20 (20%) had a neutral sentiment score of 0. The top-ranking topics for positive sentiment were *student loan payments* (197 positive sentiment versus 8,613 negative sentiment), *student loan borrowers* (38 positive sentiment versus 4,583 negative sentiment), *Supreme Court* (26 positive sentiment versus 11,908 negative sentiment), *student debt relief* (17 positive sentiment versus 8,154 negative sentiment), and *voted for student loan forgiveness* (17 positive sentiment versus 119 negative sentiment). Even though they ranked highest for positive sentiment, each of these phrases had a negative overall sentiment score. No topics listed had a positive overall sentiment score. In fact, four topics on the list - *tax money*, *health care*, *forgiving student loan debt*, *and funding a genocide* - had the maximum negative sentiment score of -99. This finding offers additional support for our second hypothesis.

A positive-negative sentiment ratio was created for phrases to compare the relationship between positive and negative sentiment. This ratio was then compared to the number of mentions. The correlation between the positive-negative sentiment ratio and mentions was calculated to be -0.078 (when rows with score of 0 for both positive and negative sentiment were assigned a ratio score of 0) or -0.122 (when rows with score of 0 for both positive and negative sentiment were excluded from the analysis). These correlations indicate a weak, negative relationship between the positive-negative sentiment ratio and mentions. When Table 3 was sorted by highest positive-negative sentiment ratio, the top five results were *voted for student loan forgiveness* (0.143), *student loan payments* (0.023), *student loan borrowers* (0.008), *millions of Americans* (0.004), and *billion in student loan debt* (0.003). Each of these phrases had a positive-negative sentiment ratio of <0.15.

The eleventh most popular phrase *#fitness Check comments for full video* was unrelated to the topic of student loans. Similarly, the seventeenth most popular phrase, *bringing him home pt3 #fitness*, was also unrelated to student loans. The topic of fitness—and why it might have shown up in the results—is expounded in subsequent parts of the paper.

Table 4 groups the popular phrases into the previously utilized three categories of student loans, government, and other/ambiguous. The average positive-negative sentiment ratio was calculated for each category. The student loans category had the highest average positive-negative sentiment ratio at 0.02 with the other two categories (other/ambiguous and government) tied with 0.001.

Table 3. Top 20 Phrases and Corresponding Sentiment Statistics

Rank	Topic Name	Mentions	Negative	Neutral	Positive	Sentiment Score	+/- Ratio
1	student loan payments	19906	8613	11095	197	-42	0.023
2	tax money	19834	19756	77	0	-99	0.000
3	health care	17883	17754	119	8	-99	0.000
4	forgiving student loan debt	17469	17427	35	5	-99	0.000
5	funding a genocide	17217	17214	2	0	-99	0.000
6	Supreme Court	13832	11908	1897	26	-85	0.002
7	student loan billing statement	12165	2092	10070	2	-17	0.001
8	Helping 18yo	11266	0	11266	0	0	0.000
9	student loan borrowers	8925	4583	4302	38	-50	0.008
10	student debt relief	8877	8154	704	17	-91	0.002
11	#fitness Check comments for full video	8811	0	8811	0	0	0.000
12	million Americans	8796	6553	2233	8	-74	0.001
13	voted for student loan forgiveness	8607	119	8469	17	-1	0.143
14	billion in student loan debt	8163	2986	5168	8	-36	0.003
15	student with his student loan	8139	0	8139	0	0	0.000
16	voted to restart	8016	4625	3390	0	-57	0.000
17	bringing him home pt3 #fitness	7638	0	7638	0	0	0.000
18	cancel your student debt	7192	3945	3246	0	-54	0.000
19	canceling an additional	6196	2305	3891	0	-37	0.000
20	millions of Americans	5597	470	5123	2	-8	0.004

Table 4. Average Phrase Positive-Negative Sentiment Ratio Across Categories

Topic Name	Mentions	Negative	Neutral	Positive	Sentiment Score	+/- Ratio
Category: Student Loans						
student loan payments	19906	8613	11095	197	-42	0.023
forgiving student loan debt	17469	17427	35	5	-99	0.000
student loan billing statement	12165	2092	10070	2	-17	0.001
student loan borrowers	8925	4583	4302	38	-50	0.008
student debt relief	8877	8154	704	17	-91	0.002
voted for student loan forgiveness	8607	119	8469	17	-1	0.143
billion in student loan debt	8163	2986	5168	8	-36	0.003
student with his student loan	8139	0	8139	0	0	0.000
cancel your student debt	7192	3945	3246	0	-54	0.000
					Average +/- Score	**0.020**
Category: Government						
tax money	19834	19756	77	0	-99	0.000
health care	17883	17754	119	8	-99	0.000
Supreme Court	13832	11908	1897	26	-85	0.002
					Average +/- Score	**0.001**
Category: Other/Ambiguous						
funding a genocide	17217	17214	2	0	-99	0.000
Helping 18yo	11266	0	11266	0	0	0.000
#fitness Check comments for full video	8811	0	8811	0	0	0.000
million Americans	8796	6553	2233	8	-74	0.001
voted to restart	8016	4625	3390	0	-57	0.000
bringing him home pt3 #fitness	7638	0	7638	0	0	0.000
canceling an additional	6196	2305	3891	0	-37	0.000
millions of Americans	5597	470	5123	2	-8	0.004
					Average +/- Score	**0.001**

Table 5 shows the top emojis used across all tweets gathered. Although this table is not directly related to a hypothesis – or attached to sentiment scores – it gives helpful insights into the mindset of the authors when writing about student loan topics. Across all tweets (tweets and retweets), the five most popular emojis were *smiling face with horns* (n = 11,704), *money bag* (n = 1,864), *police cars revolving light* (n = 1,696), *spool of thread* (n = 1,202), and *white down pointing backhand index* (n = 1,067). For tweets, the five most popular emojis were *money bag* (n = 595), *face with tears of joy* (n = 490), *loudly crying face* (n = 310), *white down pointing backhand index* (n = 94), and *police cars revolving light* (n = 55). When sorted by the greatest total number of impressions, the five most popular emojis were *smiling face with horns* (384,182,044), *white down pointing backhand index* (102,521,059), *money bag* (59,243,121), *splashing sweat symbol* (39,698,047), and *movie camera* (36,811,251). Of the ten top emojis, at least three carry a negative connotation (*smiling face with horns*, *police cars revolving light*, *loudly crying face*) with 14,068 total tweets and retweets and 392,030,725 impressions.

Table 5. Top 10 Emojis

Rank	Emoji	Label	All Tweets	Retweets	Tweets	Impressions
1	😈	smiling face with horns	11,704	11,701	2	384,182,044
2	💰	money bag	1,864	1,268	595	59,243,121
3	🚨	police cars revolving light	1,696	1,639	55	6,804,599
4	🧵	spool of thread	1,202	1,154	46	4,542,805
5	👇	white down pointing backhand index	1,067	971	94	102,521,059
6	🎥	movie camera	1,052	1,049	2	36,811,251
7	💦	splashing sweat symbol	1,001	992	8	39,698,047
8	😂	face with tears of joy	743	251	490	11,401,407
9	🤷	shrugging	734	719	14	1,468,062
10	😭	loudly crying face	668	356	310	1,044,082

Table 6 shows the top hashtags for the data gathered. Like emojis, these hashtags are not attached to sentiment scores. The top hashtag is unrelated to student loans: #fitness. Interestingly, this hashtag had 12,753 retweets but no tweets. Beyond this anomaly (addressed in the limitations section), the second to tenth hashtags were all related to student loans. The second most popular hashtag was #studentloans followed by #cancelstudentdebt. The sixth most popular hashtag was #scotus, referring to the Supreme Court of the United States. For tweets (versus retweets), the five most popular hashtags were #studentloans (1,984), #cancelstudentdebt (775), #poortax (386), #studentloan (262), and #cancelallstudentdebtnow (235). The top five hashtags had combined impressions of 34,533,799, with the list garnering 537,460,898.

Table 6. Top 10 Hashtags

Rank	Hashtag	All Tweets	Retweets	Tweets	Impressions
1	#fitness	12,753	12,753	0	501,162,722
2	#studentloans	3,567	1,582	1,984	23,392,392
3	#cancelstudentdebt	1,933	1,157	775	3,600,657
4	#studentloan	674	410	262	7,267,211
5	#poortax	446	59	386	146,290
6	#scotus	428	395	31	646,113
7	#fixstudentloans	404	368	34	342,014
8	#studentloanforgiveness	305	122	181	650,748
9	#cancelallstudentdebtnow	266	29	235	127,249
10	#cancelallstudentdebt	260	179	79	125,502

Discussion

The years and months preceding October 2023 were filled with a whirlwind of change in the federal student loan space. On March 13, 2020, the Trump Administration announced the suspension of federal student loan payments and interest. A few years later, on August 24, 2022, the Biden Administration announced blanket student loan forgiveness while payments and interest were still suspended. On June 30 of the following year the Supreme Court rejected that forgiveness proposal. In the wake of this announcement, borrowers were told that payments and interest would resume – without any balance forgiven – after over three years of no payments or interest accrual on federal student loans.

This study's analysis of X data advances a better understanding of student loan borrower sentiment during the resumption of federal student loan payments in October 2023. Our study demonstrates that borrowers experienced negative sentiment during this resumption of payments, especially without the help of forgiveness. References to student loans on the platform demonstrated a negative sentiment that greatly outpaced positive (46% negative versus 1% positive). Given the timeline outlined above, it is unsurprising that several of the most popular hashtags found in this study pointed toward student loan forgiveness as a major topic, as shown in the third, sixth, eighth, ninth, and tenth most popular hashtags (#cancelstudentdebt, #scotus, #studentloanforgiveness, #cancelallstudentdebtnow, and #cancelallstudentdebt, respectively).

In summary, both of our hypotheses were confirmed. Although neutral sentiment represented the greatest percentage across all data points (53%), negative sentiment considerably outweighed positive during the resumption of federal student loan payments. Furthermore, the topics and phrases with negative sentiment ranked higher in mentions than those with positive or neutral sentiment. All the top-ranking topics had negative sentiment scores, while phrases had higher-ranking negative sentiment scores (with negative sentiment scores taking the top seven slots and 80% of the top twenty list). Although student loan topics as a category ranked higher in average positive-negative sentiment ratios, the correlations between positive-negative sentiment ratios and mentions remained weak, pointing to a lack of bias in the findings.

Implications

Financial planners interacting with clients after the payment resumption should introduce appropriate resources to help borrowers cope with the negative feelings they may experience surrounding this area of their financial lives. Luckily for the profession, this study's findings align perfectly with the emergence of financial therapy as a bona fide discipline within the field of personal financial planning. Many practitioners in this niche, associations such as the Financial Therapy Association (FTA), and personal financial planning academic programs such as the one at Kansas State University, offer training and resources for financial planners hoping to support clients in distressing financial situations. Similarly, the CFP Board has put greater emphasis on teaching the behavioral aspects of financial planning with the addition of the "psychology of financial planning" in the CFP® Certification 2021 Principal Knowledge Topics list (CFP® Certification 2021 Principal Knowledge Topics 2021). This means the topic is now taught in all registered educational programs and tested on the CFP® exam. Whatever the preferred term (i.e., financial therapy or behavioral finance), teaching planners psychological support mechanisms has significant potential to benefit financial planning clients and student loan borrowers.

Practitioners would be wise to heed the warnings from industry thought-leaders on how student loans can delay a client's financial growth. Previously outlined studies, such as the one from Archuleta et al. (2013), demonstrate the negative aspects of carrying student loan debt, including the alarming connection between student loans and financial anxiety. In a recent article for *Business Insights*, researcher and financial therapist Dr. Megan McCoy explained how student loans can harm borrowers in two crucial ways: increasing shame and delaying financial milestones (Aguino & Richtmyer, 2023). Both can be devastating for a client's progress toward financial independence. The mounting evidence is a call to action for advisors; once and for all, student loans deserve a dedicated space in the financial plan. The costs are too great – and only increasing – for the emerging generation already saddled with student loan debt.

Limitations

This study does not compare sentiment during repayment to a period beforehand. As such, no comparisons can be made between how sentiment changed before the federal student loan interest and payment restart and after. Without the ability to compare to previous sentiment, it is impossible to decipher if negative sentiment is reflective of student loans (in general), the resumption of federal student loan payments and interest, or the collapse of Biden's student loan forgiveness initiative. Additionally, textual patterns and sentiment captured during the month of October might not be fully reflective of when student loan payments resumed as a whole, as borrowers had different due dates within the month.

This research project was largely descriptive in nature, using frequency-based analysis as the main way to uncover patterns in these gathered data. This tool was useful in identifying the overall narrative within the dataset, which can be especially helpful for exploratory research projects. However, relying too much on frequency-based analysis when using NLP can, at times, influence the interpretation of the results, introduce bias, or ignore broader context. As such, future research on this topic should use tools like regression analysis to push further into the investigation of concrete associations and relationships. Accordingly, this paper's conclusions should be interpreted in concert with those future contributions.

The results displayed in Table 6 showed that #fitness was the top hashtag across our dataset. Table 3 also showed that the phrase "#fitness Check comments for full video" was the eleventh-ranking phrase in the dataset. Unfortunately, social media data sources contain noise which can cloud the signal. Given the phrase had a sentiment score of 0, it is unlikely this result affected the testing of the study's first hypothesis, although it is probable the phrase artificially boosted overall neutral sentiment.

To gain a better understanding of the fitness phenomenon, on October 24, 2023, the authors searched the hashtags #studentloans and #fitness directly on X's website. A review of the results showed that these two hashtags regularly appeared together within large groupings of hashtags (>5). It is possible the hashtag #fitness was used along with #studentloans to boost search ranking, but perhaps more research could uncover the reasoning behind this peculiar finding.

As mentioned previously, the Brandwatch query was set to filter out pornographic content and profanities. This filtering of profanities may have artificially lowered negative sentiment for this study, even though it was notably higher than positive sentiment already. When the initial query was modified to filter out these categories, the query generator indicated this filter decreased the number of collected responses by as much as 50%.[6] If included, this data would have likely pushed negative sentiment even higher.

Conclusions

This study used Brandwatch to analyze borrower sentiment on the X platform during the resumption of federal student loan payments starting in the month of October 2023. The emotions captured by this data-gathering and analysis process were quite bleak; many borrowers expressed overwhelmingly negative emotions directed at this change. However, this negative outlook highlights an opportunity for financial planners to proactively provide adequate support for the financial and mental health of federal student loan borrowers. Given appropriate and timely action, even negative student loan events can further solidify the financial planners' positive presence in their clients' lives.

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