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Artificial Intelligence-Based Sentiment Analysis of Dynamic Message Signs that Report Fatality Numbers Using Connected Vehicle Data

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Abstract

This study presents results from sentiment analysis of Dynamic message sign (DMS) message content, focusing on messages that include numbers of road fatalities. As a traffic management tool, DMS plays a role in influencing driver behavior and assisting transportation agencies in achieving safe and efficient traffic movement. However, the psychological and behavioral effects of displaying fatality numbers on DMS remain poorly understood; hence, it is important to know the potential impacts of displaying such messages. The Iowa Department of Transportation displays the number of fatalities on a first screen, followed by a supplemental message hoping to promote safe driving; an example is "19 TRAFFIC DEATHS THIS YEAR IF YOU HAVE A SUPER BOWL DON'T DRIVE HIGH." We employ natural language processing to decode the sentiment and undertone of the supplementary message and investigate how they influence driving speeds. According to the results of a mixed effect model, drivers reduced speeds marginally upon encountering DMS fatality text with a positive sentiment with a neutral undertone. This category had the largest associated amount of speed reduction, while messages with negative sentiment with a negative undertone had the second largest amount of speed reduction, greater than other combinations, including positive sentiment with a positive undertone.

Keywords

Intelligent Transportation System, Sentiment Analysis, Dynamic Message Signs, Large Language Models, Traffic Safety, Artificial Intelligence

1. Introduction

Dynamic message signs, commonly visible on highways and roadways, are widely used to communicate with road users, including information such as detours, lane closures, congestion and other unexpected speed reductions, incidents, weather, and so on. Some jurisdictions have also employed DMS to display real-time or cumulative fatality statistics, intending to prompt more cautious driving behavior. The rationale is simple: by reminding drivers of the consequences of unsafe driving, it is thought that they will be more inclined to drive more safely, reduce their speed, become more attentive, and so on. However, the effectiveness of such messaging remains a topic of debate. A previous study has suggested that such messages might distract drivers rather than make them more attentive or that the potential emotional content of displaying the number of road fatalities may take away driver attention from the road [1]. However, another study concluded that 60.6% of drivers do notice and think positively about the DMS messages displayed [2].

The Iowa Department of Transportation (IowaDOT) uses a network of about 80 DMS signs across the state highway system, most of which are located on Interstate routes, with a few on non-interstate arterial highways. IowaDOT uses DMS with fatality messages to increase safety. The DMS displays the number of fatalities to date, which we will refer to as the primary message, and an additional supplementary message, which we refer to as the secondary message. This study aims to decode the emotional tone of secondary fatality messages and analyze how the various sentiments and undertones influence driving speeds. The secondary messages convey various sentiments with varying tones. Some are humorous statements, often referencing a seasonal event (e.g., a holiday weekend); others are more serious or may allude to the consequences of unsafe driving, such as the risk of injury.

In previous studies, the primary data source for studying the effects of DMS messaging was sensor data or segment speed data [3] [4]. The use of connected vehicle (CV) data for such studies is uncommon, with one previous study assessing the influence of DMS messages on driving behavior using CV data [5]. In this study, vehicle speeds before the DMS locations are classified as speeds before, and vehicle speeds after the DMS locations are classified as speeds after. A visibility range of 200m for the DMS is factored into the analysis, and that was considered the new location of the DMS, defining the boundary between speeds prior to and post DMS. The speed difference is calculated by taking the mean speed of vehicle waypoints for individual journeyid after the DMS and subtracting it from the mean speed of vehicle waypoints for each individual journeyid before the DMS. The journeyid defines a unique vehicle's travel, whilst the waypoints are irrespective of the journeyid.

The speed difference is analyzed alongside the message text sentiment and undertone using statistical models. The present study is the first to employ CV data to assess how the sentiment and undertone of a message text displayed impact driving speeds. Sentiment analysis is the use of natural language processing to detect opinions and attitudes expressed by authors, determining whether they are positive or negative towards specific entities (such as products, subjects, or issues) or particular aspects of those entities (like cost or quality) [6]. In this study, we defined sentiment analysis as detecting the emotion a text elicits by using natural language to obtain the sentiment and the undertone of the message. Sentiment is the overall emotion evoked when a driver encounters a DMS message, classified as positive, negative, or neutral. The undertone is defined as a more subtle aspect of the sentiment in the text, demonstrating an underlying feeling that may not be explicitly stated. The undertone was categorized as positive, negative, or neutral. We obtained the sentiment and undertone of the DMS message text using a Generative Pretrained Transformer (GPT).

This study contributes to the body of literature on DMS and traffic safety by exploring speeding behavior after encountering a DMS and examining how the sentiment and undertone of the message text influence speeding behavior. This study is relevant because it provides a way to monitor which message type influences reduced speeds from the drivers. This study also provides a way for the Department of Transportation to analyze how effective the DMS message text content is and provides a data-driven way to construct efficient message text that enhances safety on our roadways.

2. Literature Review

Sentiment analysis is the application of natural language processing (NLP) and text mining to computationally identify and understand the emotional undertones present in textual data through a classification process [7] [8]. Computer-based sentiment analysis emerged in 2004 as a shift from traditional manual analysis of opinions [9]. It has since rapidly evolved, driven by advancements in machine learning and the abundance of online data. Applications of sentiment analysis include monitoring public opinion on social media, analysis of product reviews, and improving customer service interactions [10]-[12]. While the literature on sentiment analysis in the transportation engineering discipline might be limited, there are some examples where it has been employed. One previous study aimed to address traffic congestion in Indonesian cities by encouraging the use of public transportation through sentiment analysis of opinions expressed on Twitter using a support vector machine method. The research analyzed positive and negative sentiments to identify factors influencing the hesitancy of public transport usage, with the support vector machine (SVM) model achieving an accuracy of 78.12% [13].

The use of large language models for sentiment analysis is increasing; however, there is not many studies exploring its use in traffic safety analysis. GPT has been shown to be superior in predictive performance as well as adept in handling context and sarcasm in sentiment analysis [14] [15]. One study conducted a comprehensive analysis of using various GPT models for sentiment analysis of data from twitter. The study explored prevalent difficulties encountered in sentiment analysis, such as the nuances of context comprehension and sarcasm detection. Study findings show superior proficiency of GPT models in navigating these complex aspects of sentiment analysis. The results demonstrate a marked advancement of GPT-based methods in predictive accuracy, showing over a 22% increase in F1-score relative to the best existing models [14]. Another study compared the effectiveness of GPT models against conventional machine learning models such as support vector machines and random forests for sentiment analysis. The study's outcome demonstrates that GPT-based approaches outperform traditional models such as SVM, Random Forests, and Naïve Bayes across various evaluation metrics, including F1-score, precision and accuracy [16].

Recent research has examined the impacts of DMS messaging on traffic fatalities, but there is limited guidance on the potential effects of such messages. Hall *et al*. [1] investigated the safety impacts of displaying the number of road fatalities in DMS messages in Texas. The research compared the number of crashes that occurred when the number of fatalities was displayed, which occurred during one week per month in the study period, against other weeks when such messages were not displayed. The study concluded that such messages were distracting to drivers, resulting in increased crashes when the fatality message was displayed. It was found that posting fatality statistics increased crashes by 1.35% - 4.5% within 10 km downstream of the signs. The study did not discover evidence of any benefit to safety by displaying the messages, nor was there any lasting influence during periods when the messages were not displayed. The authors speculated that the use of messages, including the number of road fatalities, which can go into the thousands in a large state such as Texas, may create an emotional "burden" to drivers, taking away from the task of driving.

Kassens-Noor *et al*. [17] revealed that positive messages, such as those evoking compassion, were more likely to induce safer driving than negative messages evoking fear. Positive messaging on how unsafe driving might affect an individual or family was more impactful. The research utilized a phone survey to evaluate the self-reported impacts of the messaging. The results indicated around 25% of respondents stated positive modifications in their driving habits after viewing the signs. Younger drivers were more prone to be reminded of safe behaviors from the messages. Lewis *et al*. [18] conducted a study that investigated the impact of message-relevant emotions in anti-drunk driving campaigns. Funny and fear-inducing ads were compared to understand their immediate and long-term effects. The research evaluated perceived influences on oneself versus others, known as the third-person effect. Factors like personal involvement, response effectiveness, and gender were also analyzed for their roles in persuasion. Findings of the study indicated that while negative ads had immediate effects, positive ads had prolonged impacts. The findings suggest the potential of positive campaigns as alternatives to negative ones in long-term persuasion.

Negative framing of messages is typically meant to increase fear in drivers and motivate drivers to make good choices on the roadways. Some studies suggest that fear seizes attention and results in better driving. Drivers in simulations responded faster to danger warnings than informative and regulatory messages [19]. A laboratory experiment with anti-speeding commercials in a simulation driving environment revealed that the fear-relief pattern effectively reduces young drivers' speed choices initially and after repeated exposure to the ad. In contrast, ads inducing fear without relief initially increased speed choices but led to reduced speeds after multiple viewings, although not as effectively as the fear-relief pattern [20]. Direct and aggressive messages captured drivers' attention more effectively than gentle or emotionally sensitive [21].

Another study analyzed income-supporting individuals' responses to social marketing campaigns that use fear, guilt, and shame to promote compliance. The findings indicate that although fear can capture attention, its excessive use can cause individuals to become emotionally desensitized [22]. A study examined the effectiveness of fear appeal messaging in discouraging distracted driving among 840 young adults. Participants viewed two anti-distracted driving PSAs and reported increased perceptions of risks posed by unsafe driving behaviors. Focus groups highlighted that current fear appeals do not arouse intense levels of fear among young adults, which may render them ineffective. Males were more skeptical that fear appeals can change behavior and more supportive of legal deterrents, while females were receptive to such messaging [23].

3. Methodology

The study obtained DMS message logs from the IowaDOT for 20 locations. The DMS data included the DMS location identifier, the time that a message was posted, and when the message was removed from display. When the DMS is not required for the display of public information (e.g. for incidents, detours, inclement weather, etc.) the signs are ordinarily left blank. However, on Fridays in 2022, a road safety awareness message was displayed. These messages consisted of a primary message stating the year-to-date number of road fatalities within the state and a secondary message as a form of communication to encourage safe driving. An example is shown in **Figure 1**. Such messages were used as the default display.

IowaDOT.

Figure 1. Example message intended to improve road safety.

3.1. Message Sentiment and Undertone

The objective of this research is to examine how the sentiment and undertone conveyed in DMS fatality message text might influence driver behavior. Recently, the use of large language models, like GPT, to identify emotions expressed in text has gained popularity in the research community. We employed Generative Pre-trained Transformer 4 (GPT-4) for sentiment analysis in this study. GPT-4 is an artificial intelligence model, an iteration of the GPT series, and an improvement on previous models such as GPT-3.5 and GPT-3. GPT-4 is designed to understand and generate human-like text based on the input it receives. It offers more refined analytical capabilities in text interpretation and emotion recognition. GPT models can grasp the irony in sentiment analysis, as confirmed by recent studies [14] [15].

For the application of GPT-4 in our analysis, we defined the objective of our study and described the specifics of our dataset. Recognizing that interpreting the DMS content as a single block (primary and secondary message) often yielded a predominantly negative sentiment mainly because of the presence of DEATHS in the primary message, we refined our approach to focus primarily on the secondary message content. By feeding GPT-4 with the DMS secondary messages, along with a well-defined context and representative examples of a complete DMS message text, we were able to obtain the sentiment and undertone accurately for our study. 31 unique fatality message text was analyzed for the study.

The sentiment of a message text was classified as "positive," "negative," or "neutral." Sentiment refers to the general emotion of a message whilst the undertone refers to the underlying emotion, which could be disguised through sarcasm. It is possible that sentiment and undertone may agree or disagree. The sentiment of a message text was classified as "positive," "negative," or "neutral." A positive message sentiment conveys encouragement, optimism, and emotions such as happiness. A negative message sentiment carries criticism, pessimism, and emotions such as fear or anger. A neutral message sentiment conveys information without any apparent emotional tone. A positive message undertone carries an encouraging subtext, suggesting solutions or positive outcomes. A negative message undertone highlights the negative outcomes and adverse consequences associated with certain driving behaviors. A neutral message undertone delivers the message without an emotional appeal.

Table 1 shows some examples of fatality messages and their sentiment. To illustrate the distribution of word choice across the various messages displayed in 2022, **Figure 2** illustrates a word cloud formed from the secondary messages. Figure 2 provides insight into the most common words used in the DMS display messages. The relative size of each word within the word cloud corresponds to its frequency of occurrence within the dataset. Prominent terms such as "drive," "driving," "phone," "buckle", etc. indicate a recurring emphasis on promoting safe and responsible driving practices in DMS messaging and a particular emphasis on discouraging cell phone use while driving.

Table 1. Fatality message text with sentiment and undertone.

Fatality Message Text	GPT-4 Sentiment	GPT-4 Undertone
3 *TRAFFIC DEATHS THIS YEAR* TEXTING & DRIVING IS NOT AUTO CORRECT	Negative	Negative
5 *TRAFFIC DEATHS THIS YEAR* LET IT GO-LET IT GO THE PHONE DOESN'T BOTHER ME ANYWAY	Neutral	Positive
17 *TRAFFIC DEATHS THIS YEAR* WATCH YOUR SPEED YOUR CAR IS NOT A BOBSLED	Neutral	Negative
24 *TRAFFIC DEATHS THIS YEAR* DEATHS GO DOWN WHEN EYES GO UP	Neutral	Positive
41 *TRAFFIC DEATHS THIS YEAR* DOES YOUR VEHICLE HAVE A RECALL? CHECK TODAY	Neutral	Neutral
52 *TRAFFIC DEATHS THIS YEAR* WHO NEEDS LUCK WHEN YOU CAN BUCKLE UP	Positive	Positive
19 *TRAFFIC DEATHS THIS YEAR* IF YOU HAVE A SUPER BOWL DON'T DRIVE HIGH	Neutral	Negative
63 *TRAFFIC DEATHS THIS YEAR* IF YOU TEXT & DRIVE TODAY'S YOUR DAY. FOOL	Negative	Negative
65 *TRAFFIC DEATHS THIS YEAR* DRIVING IS LIKE BASEBALL GET HOME... SAFE!	Positive	Positive
165 *TRAFFIC DEATHS THIS YEAR* WON'T YOU BE MY NEIGHBOR? BE KIND AT MERGE	Positive	Neutral
268 *TRAFFIC DEATHS THIS YEAR* DRIVE LIKE YOUR FRIENDS' LIVES DEPEND ON IT	Neutral	Neutral

Figure 2. Word Cloud of secondary messages from the fatality messages.

3.2. Connected Vehicle Data Processing

The study obtained CV data, specifically driver movement data, from a third-party vendor (Wejo, Inc.), which provided information on vehicle speeds and locations and had records for every 3 seconds for each unique vehicle. CV data has been used in several applications in intelligent transportation systems, such as deriving traffic performance metrics [24]-[26]. CV data were gathered between 6 am and

10 pm every other Friday of the year in 2022. The number of unique vehicles was 378,909 for the 20 DMS locations selected for analysis. A 1400m buffer is defined at these locations, and only vehicles that traveled the entire buffer are used for the analysis, with speeds ranging from 90 to 145 km/hr. We integrated the DMS logs data with CV data based on timestamps, specifically during fatality message displays. The following variables were derived from the CV data.

- Mean speed = the mean speeds of all the waypoints in the entire 1400 m buffer
- Standard deviation speed difference = standard deviation of speeds post DMS − standard deviation of speeds before DMS
- Speed difference = mean speeds post DMS − mean speeds before DMS

We selected the speed difference as our dependent variable for our statistical analysis.

Figure 3 shows the distribution of speed difference with most values clustered around zero with a mean of −0.40 mph, indicating a slight decrease in speed for the 20 DMS locations considered.

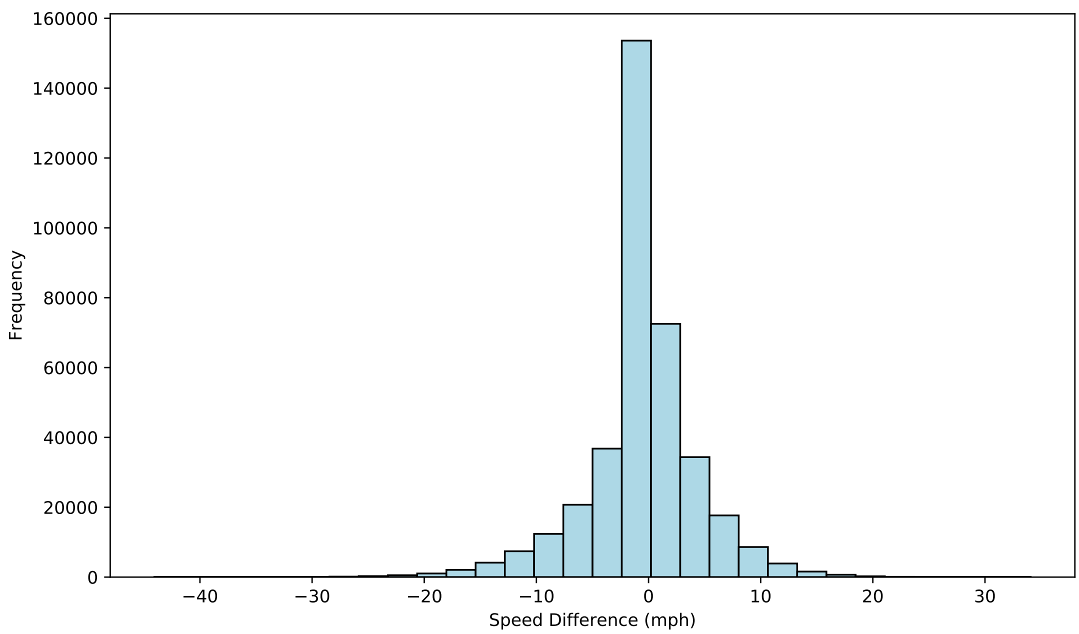

Figure 3. Distribution of speed difference.

3.3. Exploratory Data Analysis of Sentiment, Undertone, and Speed Difference

Figure 4 and Figure 5 display the speed difference for the sentiment and undertone types, respectively. The figure shows that negative sentiment results in a decrease in speed during most hours of the day; however, there are also some instances where positive sentiment results in a decrease in speed (19:00 and 22:00). At 22:00, we see a significant reduction in speed with positive sentiment compared with negative sentiment. Figure 5 illustrates neutral undertones as influencing speed reduction for most hours of the day compared to the other sentiment types.

Both figures also show some hours in the midday period have the lowest speed difference values (10:00 to 14:00), and some hours in the midday period also have the highest speed difference values (14:00 to 16:00).

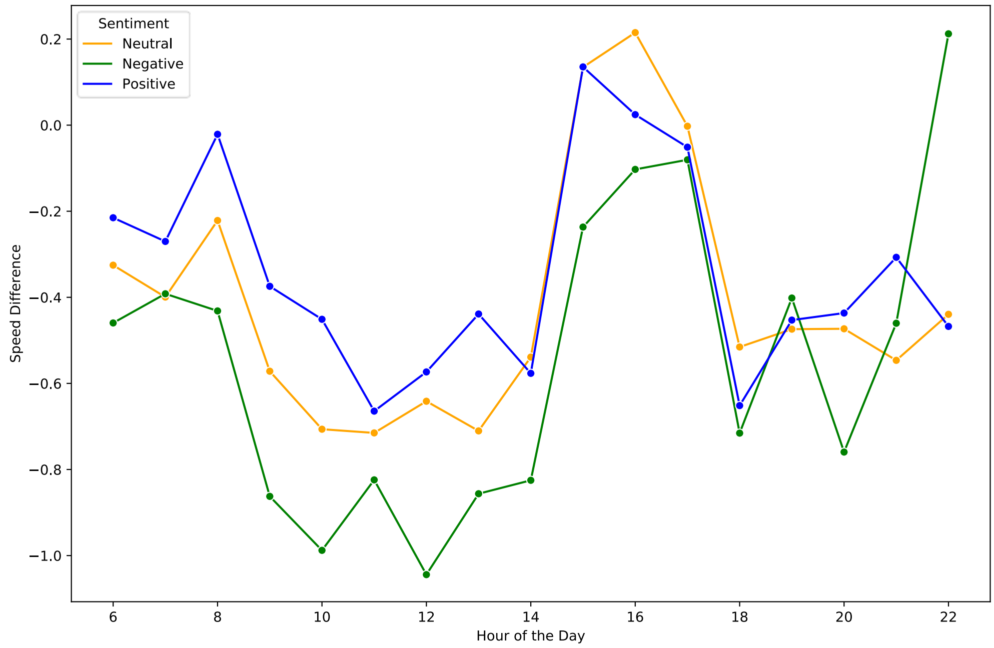

Figure 4. Speed difference of sentiment types by hour of day.

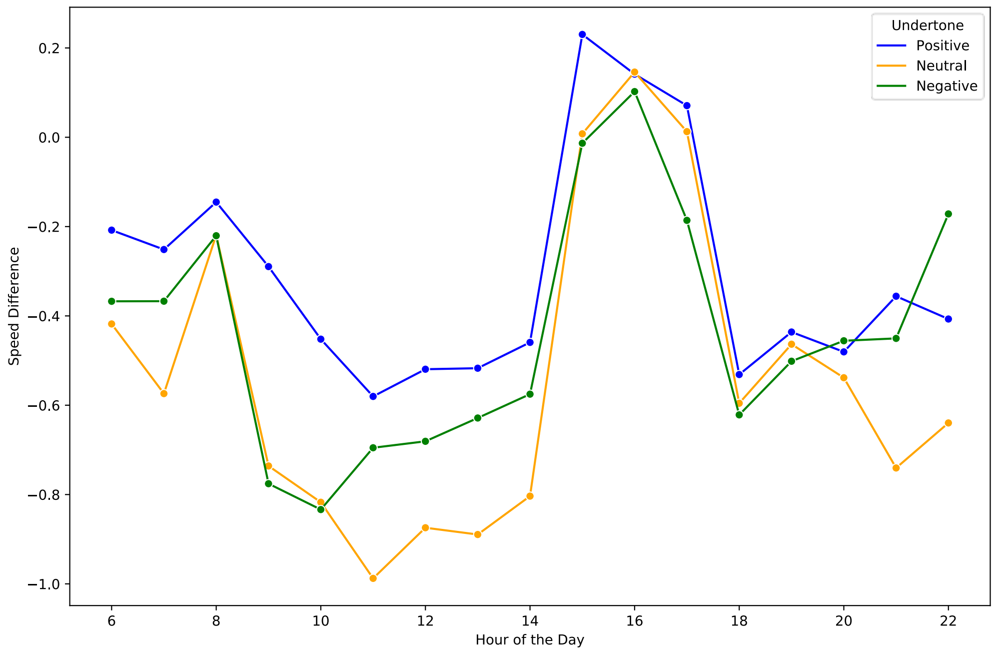

Figure 5. Speed difference of undertone types by hour of day.

The speed difference of sentiment and undertone types by hour of the day is demonstrated in **Figure 6**. The following combinations of sentiments and undertones were obtained from the data (neutral sentiment with negative undertone, neutral sentiment with neutral undertone, neutral sentiment with positive undertone, positive sentiment with neutral undertone, positive sentiment with positive undertone, and lastly, negative sentiment with negative undertone). We did not have combinations for positive sentiment with negative undertone, negative sentiment with positive undertone, and negative sentiment with neutral undertone. From **Figure 6**, we observe that positive sentiment with neutral undertone fatality message seemed to influence speed reduction more than the rest.

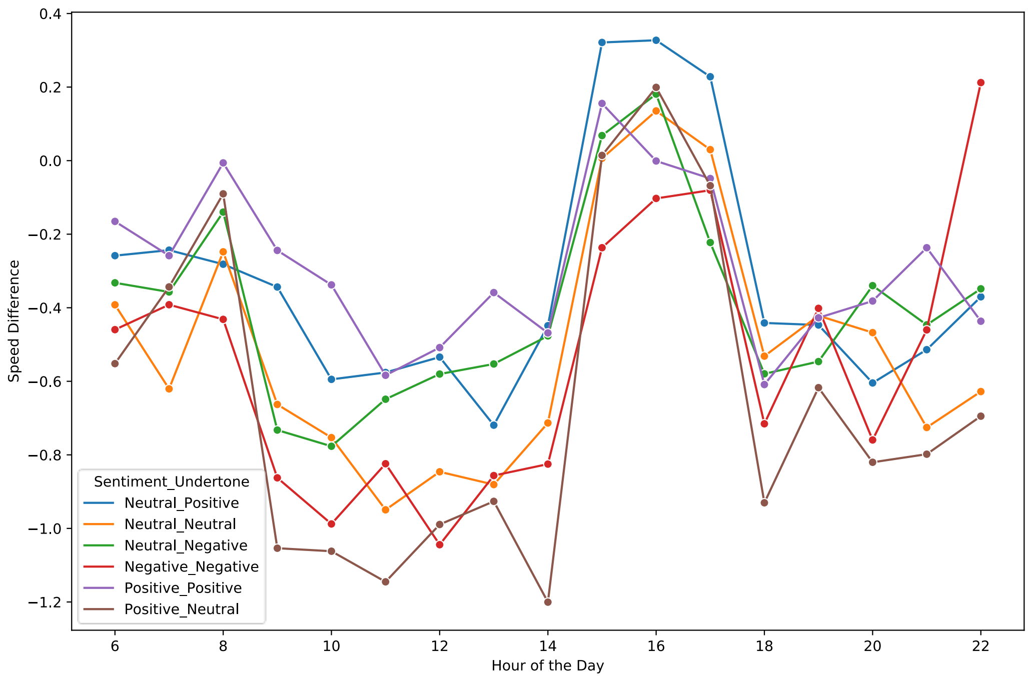

Figure 6. Speed difference of sentiment and undertone types by hour of day.

Several vehicles were exposed to different combinations of sentiment undertone message text; positive sentiment with positive undertone had the highest number of observations (**Figure 7**). Additionally, **Figure 7** suggests that all the sentiment undertone types reduced speeds slightly, as seen by the negative speed difference values.

The speed difference of the various sentiments with undertone types and the count of vehicles is demonstrated in **Figure 7**. **Figure 7** shows that DMS fatality message text with positive sentiment and neutral undertone seemed to influence speed reduction more than the rest.

Also, we observe that when we consider only the sentiment of the message text and not the undertone, negative sentiment seems to lead to a higher reduction in speeds than positive and neutral sentiment. However, the DMS fatality message texts have sarcasm and some underlying meaning; hence, it is essential to consider the sentiment and the undertone for sentiment analysis. Therefore, we used sentiment and undertone as a combined variable for our statistical analysis.

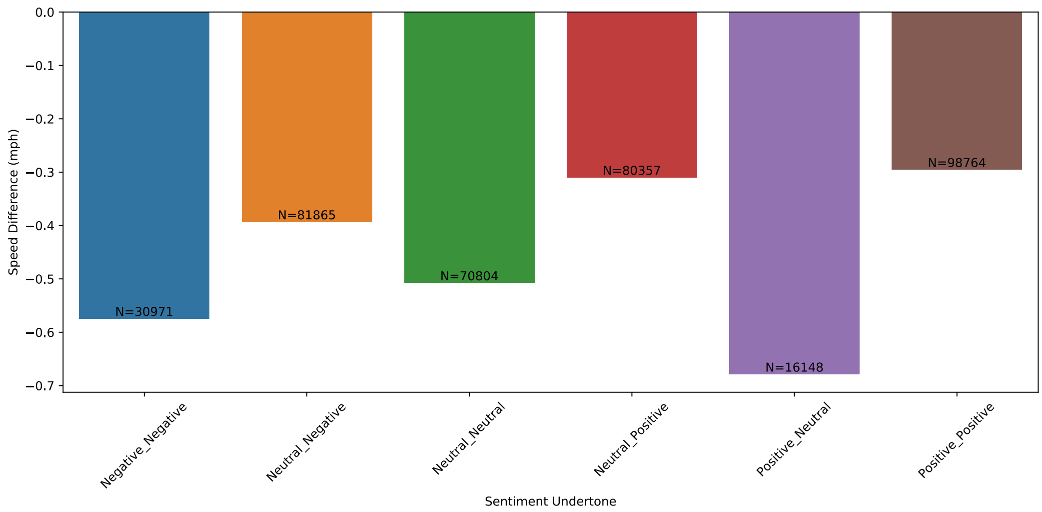

Figure 7. Speed difference by sentiment undertone with observation counts.

3.4. Statistical Analysis

The study employed the mixed effect linear model and the two-stage least square model (2SLS) for statistical analysis. The mixed effect linear model combines both fixed effects, which are measurable, and random effects, like the DMS locations where the characteristics of a DMS location can differ from another, allowing accountability for unobserved heterogeneity. We employed the 2SLS model because it addresses the endogeneity in the independent variables. One study examined endogeneity in traffic speed parameters using a three-stage least square model which was applied to comprehend the relationship between average speed, standard deviation speed, and work zone attributes [27]. The study outcomes point to a dynamic where traffic speed and its variability are shaped by work zone attributes.

The two-stage least squares model addresses potential endogeneity by using instrumental variables. Endogeneity occurs when an independent variable is correlated with the error term, possibly due to omitted variable bias, measurement error, or simultaneity [28]. Instrumental variables are used in statistical modeling to mitigate the problem of endogeneity. When explanatory variables in a model are correlated with the error term, it can lead to biased and inconsistent estimates. Instrumental variables prevent this by serving as a proxy that is correlated with the explanatory variables but not correlated with the error term. This allows for dependable estimation of causal relationships by mitigating the bias that endogeneity introduces into the estimates [29]. The 2SLS model is one of the powerful and adaptable tools to treat endogeneity [28]. The 2SLS model overcomes this by first predicting the potentially endogenous variables using the instrument variable. In the second stage, these predicted values are used in place of the original endogenous variables to estimate the effect on the dependent variable. This method ensures that the estimates are not biased by endogeneity. For the 2SLS model, the instrument variable was average speed, and the endogenous variable was standard deviation speed difference.

4. Results and Discussion

Two models were used to examine the relationships between sentiment and undertone and speed reduction: A mixed effect linear model and a two-stage least squares (2SLS) model. Both are included here for comparison, although because the 2SLS model did not yield statistically sound results, the mixed effect linear model is the main source of this study's conclusions.

4.1. Mixed Effect Linear Model

The study utilized a mixed effects model to investigate the impact of different DMS fatality message text categorized by sentiment and undertone on vehicle speeds. The sentiment and undertone were considered as one variable. To ensure each of the categories of sentiment undertone contributed equally to the model, we normalized the numeric columns using the StandardScaler from scikit-learn, standardizing the features to have a mean of 0 and a standard deviation of 1. The mixed effects model was then fitted, with speed difference as the dependent variable, sentiment and undertone (Sentiment_Undertone) as the fixed effect, and DMS location and hour of day combined as the random effect to account for group-level variability.

Our study defined speed difference as the average speeds after the DMS minus the average speeds before the DMS for unique vehicle waypoints. Hence, a negative speed difference means the DMS influenced the driver to reduce speed, and a positive speed difference means there was an increase in speed after the DMS encounter. The results of the mixed effect linear model are displayed in Table 2.

Table 2. Mixed effect linear model: sentiment and undertone as a combined variable.

Model	MixedLM		Dependent Variable		Speed difference (mph)	
No. Observations	378909		Method		REML	
No.Groups	337		Scale		0.8120	
Min. group size	1		Log-Likelihood		−499092.007	
Max. group size	6281		Converged		Yes	
Mean group size	1124.4					
	Coef.	Std. Err.	z	P > |z|	[0.025	0.975]
Intercept	−0.788	0.127	−6.216	0.000	−1.036	−0.539
Sentiment_Undertone[Neutral Negative]	0.177	0.03	5.925	0.000	0.118	0.235
Sentiment_Undertone[Neutral Neutral]	0.056	0.03	1.855	0.064	−0.003	0.116
Sentiment_Undertone[Neutral Positive]	0.221	0.03	7.448	0.000	0.163	0.28
Sentiment_Undertone[Positive Neutral]	−0.014	0.043	−0.327	0.744	−0.099	0.071
Sentiment_Undertone[Positive Positive]	0.234	0.029	8.051	0.000	0.177	0.291
Group Var	5.101	0.091				

The reference category for these comparisons was "Negative Negative" (*i.e.*, negative sentiment and negative undertone), and the coefficients in Table 2 can be interpreted as the effect of other statement categories in comparison to those. The mostly positive coefficients indicate a higher speed for four of the five categories compared to the reference category. The use of positive sentiment with negative undertones led to a slightly reduced speed (although not statistically significant). The results suggest that negative messaging may be more effective at inducing speed reductions, although the use of positive sentiment with neutral undertone may be more effective. Overall, however, it should be noted that the magnitude of the changes are small. The results agree strongly with the visualization in Figure 7.

4.2. Two-Stage Least Square Model

The results of the 2SLS are shown in Table 3. From the 2SLS model, positive sentiment and neutral undertones led to the highest speed reduction, although not statistically significant compared to the rest of the sentiment undertone types. The model also shows all sentiment undertone types led to reduced speeds as indicated by the negative coefficient. The model has a negative R-squared value, which implies the model fits the data very poorly and consequently fails to explain the variation in the speed difference. Therefore, the mixed effect model is selected to draw conclusions.

Table 3. Two-stage least square model.

Dependent Variable	Speed difference			R-squared		−13.361
Estimator	IV-2SLS			Adj. R-squared		−13.362
No.Observations	378909			F-statistic		152.65
Cov. Estimator	robust			P-value(F-stat)		0.000
				Distribution		chi(6)
	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
Sentiment_Undertone[Neutral Negative]	−0.517	0.263	−1.964	0.050	−1.033	−0.001
Sentiment_Undertone[Neutral Neutral]	−1.019	1.053	−0.968	0.333	−3.083	1.045
Sentiment_Undertone[Neutral Positive]	−0.089	0.455	−0.196	0.845	−0.981	0.803
Sentiment_Undertone[Positive Neutral]	−1.074	0.825	−1.302	0.193	−2.690	0.543
Sentiment_Undertone[Positive Positive]	−0.227	0.151	−1.503	0.133	−0.523	0.069
Std_Deviation_Diff	12.194	24.970	0.488	0.625	−36.745	61.134
Endogenous	Standard deviation speed difference	Robust Covariance	Heteroske dastic			
Instruments	Average speed	Debiased	False			

5. Conclusions

This study aimed to explore how drivers react to the sentiment of DMS fatality message text using connected vehicle data and GPT-4 for sentiment analysis of the message text. Two models were developed: a mixed effect linear model and a 2SLS model. However, the 2SLS model had a negative R-squared value, so the mixed effect linear model was used to evaluate the effects of the sentiment and undertone types and their significance.

The study results showed that positive sentiment with neutral undertone messages had the largest amount of speed reduction, as shown in **Figure 7**. The coefficients in **Table 2** agree with these trends by comparing them against the reference group with negative sentiment and negative undertone. The positive coefficients for the other four message categories suggest that negative sentiment with negative undertone yields greater speed reductions than the other four combinations (all neutral sentiments and positive sentiment with positive undertone). The study results also demonstrated that the use of sentiment or undertone independently yield considerably different results than when combined together as a single variable, as shown by differences between **Figures 4-7**.

A study by Kassens-Noor *et al*. [17] showed that message signs evoking positive emotions led to improved self-reported driving behavior. The results of our analysis partly agree in that the use of positive sentiment with neutral undertone is associated with a greater speed reduction than other options. However, we also observe that the use of negative sentiment with negative undertone yield larger speed reductions than other categories, including positive sentiment with positive undertone. This may suggest a difference between stated and revealed driver behavior.

A limitation of this study is that it does not consider the drivers' age, gender, disabilities, etc. which might influence the emotional reaction to the message content. The study findings, with additional research to confirm these initial observations and their transferability, may help lead to improved techniques for developing public messaging that would help transportation agencies create public messages that better meet their objectives. This study is to our knowledge the first to combine connected vehicle data with sentiment analysis.

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Author Contribution Statement

D. Okaidjah conceived the study, performed data analysis, and drafted the paper. C.M. Day provided guidance on the connected vehicle data analysis and revised the paper. J. Wood provided guidance on the statistical analysis of the paper.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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