Crash Reduction Analysis of Friction Improvement Surface Treatments in Georgia

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# ABSTRACT

The objective of this study was to analyze the effectiveness of three friction improvement surface treatments (FISTs)—phonolite thin polymer overlay (phonolite), lightweight aggregate (LWA), and high friction surface treatment (HFST)—in reducing horizontal curve road departure crashes in Georgia. This objective was achieved by using naive Bayes and empirical Bayes methods to develop CMFs for the three treatments based on crash and curve data provided by Georgia Department of Transportation (GDOT). The calculated CMFs show that HFST significantly reduces curve crashes, performing the best out of the three FISTs. As for the other two FISTs, while curves with phonolite did observe some crash reduction, the statistical significance of these observations is tenuous due to a small sample size and LWA did not have a large enough sample size to make any proper observations.

Further analysis on HFST was performed in order to identify the types of crash types HFST reduces the most and to create a CMF model that would show which roadway characteristics, such as AADT, affect the CMF of an HFST implementation at a curve. It was observed that HFST was most effective in reducing single vehicle and wet road crashes, and so curves that see these types of crashes often benefit from HFST. Furthermore, the generated CMF model showed that the only significant curve characteristics were crash frequency before HFST implementation, intersection-related crash frequency before HFST implementation, and AADT before HFST implementation. The former of the three has a negative relationship with the calculated CMF, while the latter two have a positive relationship with the calculated CMF. While these trends were verified with EB CMFs on filtered groups afterwards, the statistical precision of the CMF model is rather low. Regardless, the CMF model still could prove useful in future cost-benefit analyses to identify what types of curves would benefit the most from the implementation of HFST.

# INTRODUCTION

Curve related crashes are one of the main causes of fatalities in transportation in the US, as more than 25 percent of fatal crashes are associated with a horizontal curve (FHWA 2022). A majority of these curve related crashes are road departure crashes (FHWA 2022), and an available preventative measure against these types of crashes is the use of friction improvement surface treatments (FISTs). This study in particular focuses on the three FISTs implemented in Georgia: phonolite thin polymer overlay (also referred to as phonolite or as Wyoming bauxite), lightweight aggregate (LWA), and high friction surface treatment (HFST). While all three FISTs work towards the same goal of improving friction on road surfaces in order to reduce the chances of roadway departures, the three FISTs are intrinsically different in material makeup, durability, and cost. Phonolite is an epoxy-based friction improvement where phonolite aggregate is used in an epoxy-binder (Tsai et al. 2022). Light weight aggregate is a low-cost alternative aggregate being explored by Georgia Department of Transportation (GDOT) that does not require the use of a binding epoxy and is used as a resurfacing material (Tsai et al. 2022). Lastly, HFST is comprised of rough aggregates bonded to a roadway surface with an epoxy known as calcined bauxite. HFST is a proven safety measure supported by the FHWA since its addition to the Every Day Counts 2 Program list of innovations (Merritt et al. 2020), and it is usually implemented alongside other safety treatments such as signage and rumble strips.

To help mitigate curve crashes, these three types of FISTs were implemented in Georgia, starting with HFST back in 2014. Throughout 2014 to 2017, the Georgia Department of Transportation (GDOT) implemented HFST in 342 sites among districts 3, 4, 5 and 6, making Georgia the leading state in the nation for HFST usage by volume. Later in 2017, phonolite was installed at 69 sites in district 1 and LWA was installed at 10 sites in district 2. Figure 1 details the locations and times these FISTs were implemented. These HFST locations are identified from a concurrent project \_\_\_\_\_\_\_\_\_\_\_\_.

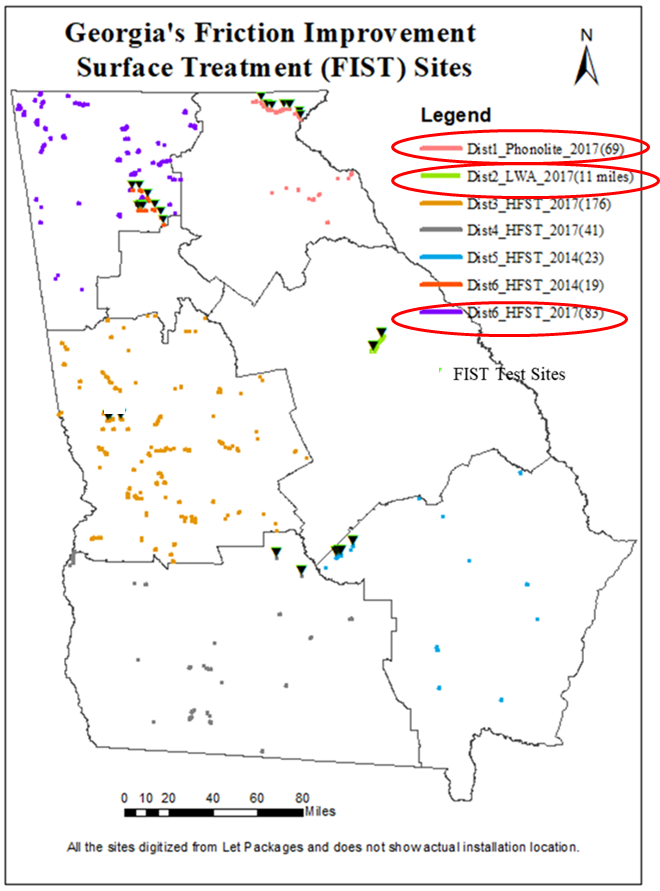


Figure 1 Locations and times of implementations of phonolite, LWA, and HFST in Georgia

In another study which collected data using a dynamic friction tester (DFT), it was discovered that HFST, currently the most used FIST in Georgia, has the best overall performance as it has the highest friction improvement at time of installation and least percentage of friction drop compared to the other two FISTs in both long-term and short-term observation periods (Tsai et al. 2022). However, HFST is comprised of rarer components, which makes it more expensive compared to the other locally made FISTs (ref). LWA was found to provide a lower level of friction improvement at time of installation (about 80% that of HFST) and had similar initial friction drops (within 3 months after installation) to HFST, but had larger friction drops in long term. Lastly, phonolite was found to provide the least amount of friction improvement (about 60% that of HFST) and showed rapid initial fiction drop but a more stable long term deterioration level like that of HFST. These differences in cost and friction performance over time will lead to different performances in crash reduction and returns on investment, and thus it is crucial to observe and understand the characteristics of these FISTs under different roadway environments to create an optimized strategy that can maximize their crash reduction efficacy while minimizing the cost.

An available way to quantify the crash reduction efficacy of each FIST is through the calculation of a crash modification factor (CMF). CMFs are used to assess the efficacy of different FISTs in terms of the proportion of the crash frequency after FIST implementation to the crash frequency before FIST implementation. For example, a CMF of 0.75 means that the FIST reduces crashes by 25% at a given location, and a CMF greater than 1.0 means this FIST is increasing the number of crashes at a given location. There are multiple methods of calculating a CMF for a FIST, and in this study the two methods used are the naïve Bayes method and the empirical Bayes (EB) method. The difference between the two methods is that the empirical Bayes method provides a higher-quality CMF which accounts for the effect of variations in other roadway features before and after FIST implementation, such as the traffic volume. This method was proven to be effective by another study that calculated empirical Bayes CMFs for curves and ramps in West Virginia, Pennsylvania, Kentucky, and Arkansas (Lyon et al. 2020). Thus far no CMFs have been developed for HFST implementations in Georgia specifically, and so it is critical to develop CMFs for Georgia-specific conditions because the roadway environment and implementation strategies in other states are not necessarily the same as that of Georgia. Similarly, no published CMFs have been developed for LWA and phonolite in Georgia.

Therefore, the objective of this study is to analyze the effectiveness of phonolite, LWA, and HFST in reducing horizontal curve road departure crashes in Georgia by using naive Bayes and empirical Bayes methods to develop CMFs. Using the calculated CMFs, the three FISTs are to be compared, the crash types that HFST reduces the most are assessed, and the roadway characteristics that have the greatest significance on the final calculated CMF are analyzed.

* Note that though friction data was recorded, high quality friction data before and after HFST implementation is not available and is not considered

# METHODOLOGY

## Data and Early Spatial Analysis

In this study, the crash data was provided by the *Numetric* platform maintained by GDOT, and curve data was provided by GDOT’s safety program (ref). The crash data included all crashes in Georgia’s districts 1, 2, and 6 from 2012 to 2020, and was formatted as a collection of points that included information such as the crash location, date of the crash, vehicles involved, and what the vehicles were doing as the collision occurred. The curve data included curve locations that implemented phonolite in district 1, LWA in district 2, and HFST in district 6, and was formatted as a collection of polylines—best described as connected lines that form the approximate shapes of a road curve, and included information such as the curve location, length, radius, deflection angle, ball-bank indicator reading, speed limit, advisory speed, and AADT.

Crashes that occurred on the same year the FIST was implemented were excluded from the CMF calculations, as it was unclear from the crash data whether these crashes occurred before or after the implementation, or even possibly during the construction of the FIST. For example, for district 6, HFST was implemented in 2017, and thus the crashes before HFST implementation included crashes from 2012 to 2016, crashes after HFST implementation included crashes from 2018 to 2020, and crashes in 2017 were ignored.

There were some initial challenges with the identification of curve AADTs, as there were multiple differing reports of AADTs. Initially, there was only one AADT associated with each curve, and therefore yearly AADTs had to be manually joined to each curve through ArcMap. (more from Ron, I’m not sure of the exact details).

Because the crash dataset included all crashes in the studied districts, there was also a need to identify which crashes occurred on curves with FIST and to discard the rest. To do so, a buffer was constructed around each curve in ArcMap—these buffers had a width of 100 ft around the road and extended 500 ft beyond the road polyline to capture all possible curve crashes. Crashes that intersected these buffers were identified as crashes that occurred on the corresponding curves and were then used as part of the CMF calculation.

Figure 2: Photo example of buffer

* 1. Describe some of the effort to attribute AADT to the curve. Describe the curve data availability.
  2. Curve data was developed from a Georgia tech application curve finder, which has given this research team a curve inventory on all GA state routes???

## Naïve Bayes Approach to Developing CMFs

The first method used to quantify the crash reduction effects of FISTs in this study is the naïve Bayes approach. The naïve Bayes approach is a straightforward way of calculating CMFs as it simply uses the proportion below in **Equation 1**:

(1)

The naïve CMFs in this study are calculated using the cumulative crash frequencies of all curves which each FIST. These cumulative naïve Bayes CMFs are then used to find which crash types should be used for the calculation of the empirical Bayes CMFs and to conduct an analysis on the significant roadway characteristics that affect the calculated CMFs the most.

## Empirical Bayes Method to Developing High Quality CMFs

A flaw of the naïve Bayes method is that the effects of external factors such as changes in traffic volume or other time trends on CMFs are not accounted for. The empirical Bayes Method can address these time trend factors in the calculations of CMFs by not just using observed crashes on a curve but by also using the predicted number of crashes generated by a prediction model, also known as a safety performance function (SPF). These predicted numbers of crashes are used to represent the number of crashes that would’ve occurred had the FIST not been applied to the curve, and the observed crashes are weighed against these predictions to adjust the CMF.

For example, a curve that had a FIST implemented but also a significantly higher traffic volume could possibly observe a higher number of crashes after the FIST. Using a naïve Bayes approach, the number of crashes would suggest that the FIST caused an increase in crashes. However, an empirical Bayes approach would weigh the observed crashes against the prediction—which would predict that crashes should increase due to increased traffic and not because of the FIST—and thus decrease the final calculated EB CMF accordingly. The EB methodology in this study is derived from the FHWA’s *A Guide to Developing Quality Crash Modification Factors* (FHWA 2010).

### Development of Safety Performance Function Prediction Models

As noted in the previous section, the safety performance function (SPF) is used to calculate the predicted number of crashes needed in order to calculate the EB CMF. The predicted crashes are calculated based on the curve characteristics, which for this study includes whether the road is divided, the natural log of the curves’ deflection angle, the curve length, the natural log of the AADT of the curve, the natural log of the ball bank indicator (BBI) measurement of the curve, and the speed difference between the posted speed limit and the advisory curve speed limit. The calculation for the predicted number of crashes per year (P) given certain curve characteristics (Cn) and coefficients for those characteristics (Yn) is as follows in **Equation 2**:

(2)

The coefficients are found through (Need help explaining the process of finding model coefficients). The negative binomial model outputs coefficients that are attributed to a curve characteristic. A separate set of coefficients is created for each crash type identified after the calculation of the naïve Bayes CMFs.

* 1. 5 prediction models are developed.
  2. Models assessed based on goodness of fit,p-value of variables, and preliminary basis of a concurrent study to develop high quality SPFs for network screening purposes (reference my paper)
  3. SPFs are developed for rural curves in GDOT districts 1,2, and 6 the dependent variable of the spf is the crash frequency on each curve

### Calculation of the EB CMF

To weigh the observed number of crashes against the predicted number crashes generated by the SPF, the two values are first combined into an expected number of crashes for both before and after implementation of FIST. The expected crashes before FIST implementation (Ebefore) is calculated using the cumulative crash frequency before FIST implementation for all curves (O), the cumulative predicted crash frequency before FIST implementation for all curves (P), and a weight *w* in the following **Equation 3**:

(3)

The weight *w* can be calculated by using *k*, the dispersion of the SPF prediction model, and the following **Equation 4**:

(4)

The expected number of crashes after the FIST is found using the following **Equation 5**:

(5)

The variance (*V*) of the expected crashes after is then found using the following **Equation 6**:

(6)

Using these values, the final EB CMF is calculated using **Equation 7**:

(7)

The calculation of the standard error of the EB CMF is as follows in **Equation 8**:

(8)

Multiple CMFs are calculated for each FIST using the crash types found in the naïve Bayes CMF crash type analysis.

## Modeling naïve CMFs as functions of the roadway environment

After the naïve Bayes CMFs are calculated, a regression analysis in R is performed to understand the effect of different roadway features on those CMFs and to propose a potential model for predicting future CMFs given a set of roadway features. In this study, this analysis is limited to CMFs for HFST in district 6. The roadway features used for this analysis are selected on the basis that these features should be accessible to engineers before implementing the FIST. Thus, the roadway features selected for the analysis are the speed limit of the curve, the curve length, the BBI measurement of the curve, the average AADT of the curve before HFST implementation, the intersection-related crash frequency of the before HFST implementation, and the crash frequency of the curve before HFST implementation. A multiple linear regression model that uses the calculated naïve CMFs as the dependent variable and the selected roadway features as the independent variables is generated, and a backward and forward feature selection process is performed to find the significant roadway features. The multiple linear regression, given curve characteristics Cn and coefficients Zn, takes the form of **Equation 9**:

The variables that are found to have significant effect on the calculated EB CMFs are then isolated by grouping curves based on those variables and then calculating separate EB CMFs for each group. For example, if curve length was identified as a significant variable, then the curves would be grouped based on longer or shorter curve lengths, and a separate EB CMF would be calculated for each curve length group.

# RESULTS

## Naïve Bayes CMFs

The preliminary investigations with the naïve Bayes CMFs led to four different crash types to investigate with EB CMFs: a CMF with all crashes, a CMF with only single vehicle crashes, a CMF with only crashes with the “Negotiating a curve” maneuver, and a CMF with only crashes with wet road conditions were calculated. The crash frequency before FIST implementation, crash frequency after FIST implementation, and calculated naïve Bayes CMFs for each FIST are summarized below in table 1 below.

Table 1: Crash frequencies and naïve Bayes CMFs of studied FISTs

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Filter | Crash frequency before FIST  implementation  (2013-2016) in crashes/year | Crash frequency after FIST implementation  (2018-2020) in crashes/year | CMF Value |
| Phonolite/Wyoming Bauxite | All Crashes | 41.75 | 40.00 | 0.958 |
| Single Vehicle | 27.25 | 24.67 | 0.905 |
| Curve | 27.25 | 20.67 | 0.758 |
| Wet Road | 8.75 | 9.33 | 1.067 |
| LWA | All Crashes | 5 | 6.33 | 1.267 |
| Single Vehicle | 3.75 | 3.67 | 0.978 |
| Curve | 1.00 | 0.33 | 0.333 |
| Wet Road | 0.25 | 1.00 | 4.00 |
| HFST | All Crashes | 167.00 | 113.67 | 0.681 |
| Single Vehicle | 111.50 | 61.33 | 0.550 |
| Curve | 117.00 | 72.00 | 0.615 |
| Wet Road | 56.25 | 26 | 0.462 |

## Developed SPFs

The coefficients of the SPF function for all crashes, single vehicles crashes only, curve crashes only, and wet road crashes only are listed below in tables 2 to 5.

Table 2: Total crashes SPF coefficients

|  |  |  |  |
| --- | --- | --- | --- |
| Label | Estimate in ln(crashes/year) | Estimate divided by number of years | P value |
| Intercept | -4.345000 | -0.543125 | < 2e-16 \*\*\* |
| Divided road | 0.332100 | 0.0415125 | 1.32e-08 \*\*\* |
| Natural log of deflection angle | 0.247400 | 0.030925 | 2.67e-11 \*\*\* |
| Length | 0.000221 | 2.76375E-05 | 1.18e-10 \*\*\* |
| Natural log of AADT | 0.649600 | 0.0812 | < 2e-16 \*\*\* |
| Dispersion | 1.233000 |  | |
| Years | 8 |
| R2 | 0.491146 |

Table 3: Single vehicle crashes SPF coefficients

|  |  |  |  |
| --- | --- | --- | --- |
| Label | Estimate in ln(crashes/year) | Estimate divided by number of years | P value |
| Intercept | 2.878000 | 0.35975 | < 2e-16 \*\*\* |
| Divided road | -0.270400 | -0.0338 | 3.95e-08 \*\*\* |
| Natural log of deflection angle | 0.141300 | 0.0176625 | 0.000409 \*\*\* |
| Length | 0.000408 | 5.09625E-05 | < 2e-16 \*\*\* |
| Natural log of AADT | 0.378700 | 0.0473375 | < 2e-16 \*\*\* |
| Natural log of BBI | 0.146800 | 0.01835 | 5.22e-07 \*\*\* |
| Speed limit and advisory speed difference | 0.015740 | 0.0019675 | 1.43e-05 \*\*\* |
| Dispersion | 2.604400 |  | |
| Years | 8 |
| R2 | 0.323600 |

Table 4: Curve crashes SPF coefficients

|  |  |  |  |
| --- | --- | --- | --- |
| Label | Estimate in ln(crashes/year) | Estimate divided by number of years | P value |
| Intercept | -5.882000 | -0.73525 | < 2e-16 \*\*\* |
| Divided road | -0.269500 | -0.0336875 | 2.59e-06 \*\*\* |
| Natural log of deflection angle | 0.630000 | 0.07875 | < 2e-16 \*\*\* |
| Length | 0.000093 | 1.16363E-05 | 0.0198 \* |
| Natural log of AADT | 0.497900 | 0.0622375 | < 2e-16 \*\*\* |
| Natural log of BBI | 0.254800 | 0.03185 | 4.94e-14 \*\*\* |
| Speed limit and advisory speed difference | 0.006123 | 0.000765375 | 0.1264 |
| Dispersion | 2.046300 |  | |
| Years | 8 |
| R2 | 0.422435 |

Table 5: Wet road crashes SPF coefficients

|  |  |  |  |
| --- | --- | --- | --- |
| Label | Estimate in ln(crashes/year) | Estimate divided by number of years | P value |
| Intercept | -5.932000 | -0.7415 | < 2e-16 \*\*\* |
| Natural log of deflection angle | 0.245500 | 0.0306875 | 8.02e-05 \*\*\* |
| Length | 0.000219 | 0.000027425 | 3.33e-05 \*\*\* |
| Natural log of AADT | 0.654000 | 0.08175 | < 2e-16 \*\*\* |
| Speed limit and advisory speed difference | 0.021210 | 0.00265125 | 0.000286 \*\*\* |
| Dispersion | 0.887400 |  | |
| Years | 8 |
| R2 | 0.295964 |

## Empirical Bayes CMFs

The summary of the calculated Empirical Bayes CMFs is shown below in table 6. No Empirical Bayes CMFs were calculated for curves in District 2 with LWA FIST due to the lack of sufficient data.

Table 6: Summary table of calculated EB CMFs

|  |  |  |  |
| --- | --- | --- | --- |
|  | Filter | Empirical Bayes CMF | Standard Error |
| Phonolite/Wyoming bauxite | All crashes | 0.9163 | 0.1427 |
| Single vehicle crashes | 0.8576 | 0.1642 |
| Curve crashes | 0.7172 | 0.1372 |
| Wet surface crashes | 0.8616 | 0.2752 |
| HFST | All crashes | 0.6719 | 0.0521 |
| Single vehicle crashes | 0.5421 | 0.0513 |
| Curve crashes | 0.6065 | 0.0562 |
| Wet surface crashes | 0.4454 | 0.0592 |

## Significant Factors of HFST CMFs

The summary of the found significant road features to the calculated CMFs for HFST are below in table 7. Figures 3 to 5 are the regression plots made for these significant road features.

Table 7: Significance of roadway factors on the calculated EB CMFs

|  |  |  |
| --- | --- | --- |
| Significant Roadway Features | Model coefficient | P-Value |
| Average AADT Before FIST | 6.274×10-5 | 0.00026 |
| Intersection Related Crash Frequency Before FIST | 6.865×10-2 | 0.01441 |
| Crash Frequency Before FIST | -1.515×10-1 | 0.00140 |
|  | | |
| R2 value | 0.1052 | |

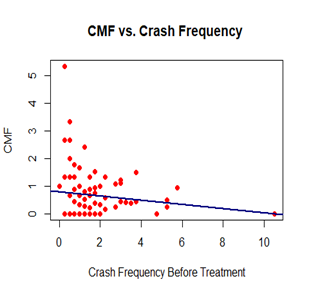


Figure 3 [desc]

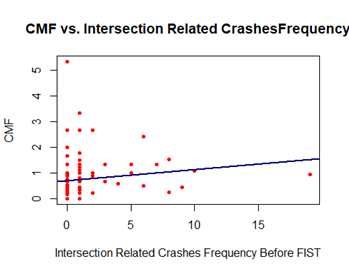


Figure 4 [desc]

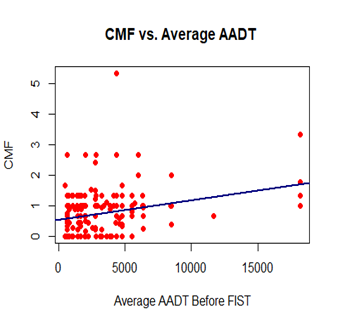


Figure 5 [desc]

The curves in district 6 were grouped based on the significant variables of crash frequency before FIST implementation and average AADT, and the EB CMFs for each group are listed below in table 8.

Table 8: District 6 HFST EB CMFs for differing curve characteristics

|  |  |  |
| --- | --- | --- |
|  | CMF (Standard Error) | |
|  | AADT ≤ 2000 | AADT > 2000 |
| Crashes Before FIST Implementation ≤ 3 | 0.8709 (0.1634) | 0.9500 (0.2052) |
| Crashes Before FIST Implementation > 3 | 0.4190 (0.1055) | 0.5766 (0.0584) |

The crash data in district 6 was filtered to intersection-related or not intersection-related crashes, and two more EB CMFs were calculated with these filters shown below in table 9.

Table 9: District 6 HFST EB CMFs for intersection vs. non-intersection crashes

|  |  |  |
| --- | --- | --- |
| Filter | Intersection crashes | Non-intersection crashes |
| CMF | 0.9646 | 0.6265 |
| Standard Error | 0.2259 | 0.0513 |

# DISCUSSION

## Use of Empirical Bayes Method

Through the calculations demonstrated in the methodology, the EB method helped account for the correlation between the general increase of traffic and the general increase of crashes on the monitored curves. Thus, the adjusted CMFs were lower than the original naïve Bayes method CMFs, and the EB method realized more benefit of the FISTs. As seen in tables 1 and 6, this trend holds true for all CMFs calculated regardless of FIST or the type of crash filter, and the greatest benefits to CMFs were seen for phonolite—especially in the CMF for wet road crashes, which improved from a naïve CMF of 1.0667 to an EB CMF of 0.8616.

However, the standard errors for the phonolite EB CMFs are greater than the difference between the EB CMFs and the naïve CMFs in all cases, indicating that the gains made through using the EB method aren’t statistically significant for phonolite. In addition, the range for standard error for certain phonolite EB CMFs even suggest that the phonolite could have caused an increase in crashes. On the other hand, while the standard errors for the HFST EB CMFs are greater than the gains made through the EB method, the range for standard error for all HFST EB CMFs are well under 1.0 and therefore still show that the implementation of HFST led to a crash reduction.

## Crash Types

Because not all crashes on curves are necessarily affected by or related to the FIST implemented there—such as crashes caused by driver error or distraction—three distinct filters were applied to the crashes for each FIST to gain a clearer perspective of the FISTs effect on crashes where FIST does have relevance. These filters were single vehicle crashes, related crashes (where the vehicle maneuver(s) include a vehicle that is “Negotiating a curve” in the data), and wet road crashes. These filters revealed significant trends in their respective CMFs: for example, for HFST, the single vehicle crash CMF and wet road crash CMF are lower than the all crashes CMF, regardless of whether the CMF was calculated using the naïve Bayes or empirical Bayes method. This indicates that HFST is especially effective in reducing single vehicle and wet road crashes on curves. Similar trends are not seen in neither the naïve or the empirical CMFs for phonolite and LWA.

## CMF Model

It was found that there are three significant roadway features, which are crash frequency before HFST implementation, intersection-related crash frequency before HFST implementation, and average AADT before HFST implementation, which have coefficients of -1.515×10-1, 6.865×10-2, 6.274×10-5, and P-values of 0.00026, 0.01441, 0.0014, respectively. Other typical roadway features such as curve radius, BBI, speed limit, and curve length were abandoned in the model during the feature selection process as they were found to be uncorrelated and insignificant in predicting a CMF.

The latter two significant factors—average AADT before HFST and intersection-related crash frequency before HFST—are features with positive coefficients, which means that an increase in these factors correlate with an increase of the final calculated CMF. This indicates that HFST might be less effective in curves with high AADT and/or are located near an intersection with a high crash frequency history. This makes sense intuitively, as higher traffic volume and intersection conflict points create opportunities for crashes that aren’t mitigated by the increased friction from FISTs. Crash frequency before FIST, on the other hand, has a negative coefficient in the multiple linear regression model, indicating that curves that have a higher prior crash frequency tend to result in lower CMFs, or a greater improvement in crash reduction. It is worth noting that this trend might simply be because curves that have small crash frequency have little room for improvement and thus the benefit for implementing HFST might be less visible through the crash data. Future studies can expand upon these findings by locating a threshold for optimizing Cost/Benefit for different types of FISTs implementation based on prior crash frequency or traffic volume.

To confirm these trends, curves in district 6 were first organized into groups based on their AADT and crash frequency before HFST implementation. Each curve was assigned an AADT rating, which would be either low AADT (≤ 2000 vehicles per day) or high AADT (> 2000 vehicles per day), and a prior crash frequency rating, which would be either low prior crash frequency (≤ 3 crashes in the years before FIST) or high prior crash frequency (> 3 crashes in the years before FIST). The AADT groups were derived from the GDOT Design Policy Manual, which designates roads with an AADT less than 2000 vehicles per day as low-volume rural collectors (GDOT 2022) and the crash frequency groups were derived from the median number of crashes before FIST implementation, which was found to be 3 crashes per year. The calculated EB CMFs for each of these groups in table 8 reveal the same trends: curves with higher AADTs before HFST implementation had higher CMFs, and curves with higher crash frequency before HFST implementation had lower CMFs.

Lastly, to confirm the positive relationship between intersection-related crash frequency before HFST implementation and the calculated CMF, the crash data was classified as either intersection related or not intersection related based on whether the crash included the term “Turning” anywhere in the vehicle maneuvers field. The trend also held true in this case, as table 9 shows that the CMF calculated for intersection related crashes is significantly higher than the CMF calculated for not intersection related crashes.

However, the low R2 value for the CMF model in table 7, 0.1052, indicates that the CMF model has a very low precision and can only accurately capture the general trends described above. Regardless, the CMF model still could prove useful in identifying the types of curves that would benefit the most from the implementation of HFST.

## Different Materials

Out of the three FISTs presented in this study, HFST by far performed the best. The Empirical Bayes CMFs show that HFST reduces crashes of all types by about 33%, and even more significantly, that it reduces wet road crashes by about 55%. Phonolite was significantly less effective, with its Empirical Bayes CMFs suggesting that it reduces crashes of all types by less than 9%. These findings correlate to the observed friction performance of these materials over time, where phonolite only has about 60% of the initial friction of HFST (Tsai et al. 2022). This correlation further supports that friction is an important factor in curve crashes and that greater friction performance helps mitigate curve crashes. There were no conclusive findings for the performance of LWA, however, due to the lack of crash data.

## COVID-19 Impact on EB CMFs

There were initial concerns that the decreased traffic volume during the COVID-19 pandemic would cause significant changes to the calculated CMFs. However, after comparing EB CMFs that included data from the year 2020 to EB CMFs that excluded said data, only a minimal difference was noticed, suggesting that the sample size of the data was large enough to mitigate the effect of possible traffic volume variations during the pandemic. Since crashes are rare events, it is more advantageous to utilize more years of data, and thus data from the year 2020 was utilized to increase the sample size of data after FIST implementation to at least three years of data.

# CONCLUSION

The naïve Bayes and empirical Bayes method was used in order to calculate the CMFs of phonolite, LWA, and HFST curve sites in Georgia. For both naïve and empirical Bayes CMFs, HFST performs the best out of the three FISTs, which correlate with its superior friction performance found in other studies (Tsai et al. 2022). While curves with phonolite did observe some crash reduction, the statistical significance of these observations is tenuous due to a small sample size. LWA did not have a large enough sample size to make any proper observations.

It was observed that HFST was most effective in reducing single vehicle and wet road crashes, and so curves that see these types of crashes often benefit from HFST. Furthermore, the multiple linear regression model performed using the calculated HFST naïve Bayes CMFs as the dependent variable and the curve characteristics as the independent variables found that the only significant curve characteristics were crash frequency before HFST implementation, intersection-related crash frequency before HFST implementation, and AADT before HFST implementation. The former of the three curve characteristics has a negative relationship with the calculated CMF, while the latter two curve characteristics have a positive relationship with the calculated CMF. While these trends were verified with EB CMFs on filtered groups afterwards, the statistical precision of the CMF model is rather low. A larger HFST crash data sample size can possibly remediate this concern.

The main challenge for this study was that the analysis for phonolite and LWA could not be as robust as the analysis for HFST due their comparatively small sample sizes. This is especially true for LWA, where there wasn’t enough data to warrant the use of the EB method for CMFs. Other than looking for larger sample sizes for more robust analysis, further studies can also explore cost-benefit analyses of the three FISTs in Georgia, especially for the less-documented phonolite and LWA.

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# AUTHOR CONTRIBUTIONS

The author’s confirmed contribution to the paper are as follows: study conception and design: R. Knezevich, Y. Tsai; data collection: Ronald Knezevich; analysis and interpretation of results: M. Liu, J. Li, R. Knezevich; draft manuscript preparation: M. Liu, J. Li. All authors reviewed the results and approved the final version of the manuscript.

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