**Relationship between Programmed Heavy Vehicle Inspections and Traffic Safety**

**Behrang Assemi**¹, **Mark Hickman**², and **Alexander Paz**³

**Abstract**

Heavy vehicle crashes incur significant economic and social costs. Although most crashes are considered to be related to driver error, the effects of vehicle defects are major in many crashes. Therefore, various vehicle inspections including Queensland’s Certificate of Inspection (COI) scheme have been implemented to improve the safety of heavy vehicles. This study analyzes the trends of heavy vehicle crashes and their relationships with COI results. Longitudinal data provided by Queensland’s Department of Transport and Main Roads for the period of June 2009 through December 2013 were used to perform the analyses. The data include 474,640 programmed inspections and 2,274 crashes in which heavy vehicles were involved. The results show significant relationships between the monthly average inspection failure rate as well as the monthly average failure severity level, and the total number of heavy vehicle crashes. The results also reveal significant relationships between the monthly average inspection failure rate, average vehicle age, as well as monthly average mean maximum temperature, and the number of defect-related crashes. The implications of these results are discussed with respect to heavy vehicle safety policies.

During 2016, heavy vehicles were involved in 191 fatal crashes with 213 deaths across Australia (1). Heavy vehicles were involved in almost 16% of all fatal crashes, while they represent only 2.4% of the total number of registered vehicles and 7% of the total vehicle kilometers traveled (VKT) (2). Heavy vehicle crashes are usually associated with more severe injuries (2).

A careful examination of heavy vehicles which were involved in fatal crashes and had performance issues showed that about one-third of them could be identified, if they were inspected exactly before the crashes (3). Thus, heavy vehicle inspections including Queensland’s Certificate of Inspection (COI) scheme have been implemented to improve the safety of heavy vehicles, specifically by decreasing defect-related crashes (4–9).

While a few studies (e.g., Elvik [10]) have found correlations among inspections of heavy vehicles, a decline in vehicle defects, and total number of heavy vehicle crashes, a recent review of the existing literature shows that there is little relevant empirical research (11). Accordingly, this research investigated the longitudinal relationship between programmed heavy vehicle inspections and heavy vehicle crashes in Queensland. In particular, this research aimed to find any potential correlation between programmed heavy vehicle inspection results and the total number of heavy vehicle crashes as well as the number of crashes caused by heavy vehicle defects over a five-year period.

Accordingly, two separate models were developed using the time series data of programmed heavy vehicle inspections and heavy vehicle crashes in Queensland, for the period June 2009 through December 2013. Considering the non-stationary nature of the observations in the dataset, an autoregressive integrated moving average (ARIMA) model was fitted to the time series data including all heavy vehicle crashes. In addition, a linear regression model was fitted to the time series data of defect-related heavy vehicle crashes.

The remainder of the paper is organized as follows. The next section presents a summary of the literature on heavy vehicle inspections and road safety. Then, the data

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used in this study and the corresponding analysis methods are described. Next, the analysis results are presented and discussed relative to the literature. Finally, the study insights for both researchers and practitioners are summarized.

**Literature Review**

As defined by the Australian Heavy Vehicle National Law (HVNL), a “heavy vehicle” is a vehicle with a gross (combination) mass of 4.5 tonnes or above; this definition includes rigid trucks, articulated trucks and buses (12). Considering only trucks (rigid and articulated), there were more than 400,000 heavy vehicles registered across Australia in 2011, increasing to more than 430,000 as of 2016 (13). The total VKT of heavy vehicles (i.e., articulated, rigid and other trucks) increased from 3.54 to 4.09 billion VKT for the financial years ending 30 June 2010 and 2014, respectively (14). These vehicles moved 26,000 tonne kilometers of freight annually for every person in the country (15). While the overall safety of the freight industry has improved over the last decade, heavy vehicles are still responsible every year for more than 200 and 1,500 crashes involving fatalities and hospitalization, respectively (15).

Most heavy vehicle crashes are considered to be primarily caused by driver error. However, the effect of vehicle defects is evident in many collisions (16). A recent study in Australia showed that vehicle defects are causing 5% of the total heavy vehicle crashes (17). Therefore, vehicle inspections, including Queensland’s COI scheme, are crucial for the effective management of heavy vehicles’ safety (4).

The COI, originally introduced in 1995, requires any vehicles with a high likelihood of non-compliance with safety standards, as well as high-use vehicles registered in Queensland, to undergo a programmed or periodic inspection every 6 or 12 months (depending on vehicle type) (7, 8). These vehicles include heavy vehicles, tow trucks, buses, taxis, and limousines, although such a vehicle can be exempt from COI, if it is only used in a limited number of exempt areas or it is participating in the maintenance module of the National Heavy Vehicle Accreditation Scheme (NHVAS) (7, 18). A COI is issued for such vehicles, if they meet minimum safety standards; any defects should be fixed and the vehicle need to be reinspected, if issues are identified during a vehicle’s programmed inspection. Driving such vehicles without a current COI is an offense, unless they are driven by the most direct route from the garaging address to a place of repair (12).

A review of the literature shows that there is little empirical research about the effects of programmed inspections on heavy vehicle defects, and the number of crashes and casualties (9, 11, 19). Previous studies have shown the overall effectiveness of roadside/random inspections in reducing vehicle-defect-related crashes (20). Moreover, some studies (e.g., Elvik [10]) have found correlations between programmed inspections and a decline in heavy vehicle defects as well as the total number of associated crashes. Das et al. (9) found that the states with inspection anticipate a smaller number of monthly vehicle complaints and complaint-induced crashes than the states without inspection in the United States. This shows that the mandatory vehicle inspection programs may have a positive effect on safety.

Blows et al. (21) showed that not having a current certificate of inspection is associated with the likelihood of involvement in a crash with injury or fatality in Auckland, New Zealand. Moreover, according to Christensen and Elvik (22), heavy vehicle drivers who are less concerned about the safety of their vehicles, as evidenced by higher inspection failures, have a higher crash rate regardless of the technical condition of their vehicles.

Previous studies have shown that inspection interval has a potentially significant effect on detected vehicle defects and road safety. For example, Keall and Newstead (4) showed that reducing the inspection interval from 12 months to six months improves safety outcomes by 8% (95% confidence interval: 0.4%–15%) and 13.5% (95% confidence interval: 12.8%–14.2%), respectively, by decreasing relevant injury crash rates and vehicle defects as a contributing factor to crashes. Although these findings are not conclusive given the large confidence intervals, such results suggest that there is a potentially significant effect of inspection intervals on safety outcomes.

**Method**

**Data**

The heavy vehicle inspection and crash datasets used in this study were provided by Queensland Department of Transport and Main Roads (TMR). These datasets include heavy vehicle programmed inspection results from June 2009 through December 2013, and the corresponding road crash data. Figure 1 illustrates the distribution of heavy vehicle crashes across Queensland during the analysis period; as expected, most crashes occurred across urban centers.

These datasets include a total of 474,640 inspections and 2,274 crashes involving heavy vehicles. Both single- and multi-vehicle crashes were considered together in the analysis, as we did not find any significant differences between the results of the time series analysis of the two categories, when considered separately. Each record in the crash dataset includes the potential contributing factors, one of which is a vehicle defect.
Each inspection record includes date, the triggering inspection id (if the inspection is a follow-up for a failed inspection), the inspection result ("Pass" or "Fail"), and the failure severity level if the inspection result was “Fail.” The failure severity levels assigned to vehicles include: Self-clearing (level 1), Minor - no label affixed (level 2), Major - label affixed (level 3), and Dangerous - label affixed (level 4).

A preliminary investigation of the data reveals that the mean inspection failure rate, the total number of crashes, and the number of crashes caused by a vehicle defect have decreased over the 3.5 years. Concurrently, the average age of vehicles has increased over this period, as shown in Figure 2. Therefore, the data suggest a potential effect of programmed inspections on reducing vehicle defects, as evidenced by the declining mean of monthly inspection failure rates and consequently the number of defect-related crashes.

Weather conditions are also considered to be an influential factor in heavy vehicle crashes. The weather data used in this study were obtained from the website of the Australian Bureau of Meteorology (23). However, Queensland has a very large area (1.853 million km\(^2\)) with climate conditions varying widely by region. Figure 3 shows the state climate zones, as identified by the Australian Building Codes Board (24). Given the density distribution of heavy vehicle crashes across the state (shown in Figure 1) and the climate zones, five cities were selected as a representative sample, including: Townsville (zone 1), Rockhampton (zone 2), Roma (zone 3), Brisbane (zone 4) and Toowoomba (zone 5). For each city, the monthly mean maximum temperature (°C) and monthly rainfall (mm) data were collected. The arithmetic mean of each variable across these five cities is considered as an indicator of the overall weather condition across Queensland.

Figure 4 illustrates the monthly mean maximum temperature (°C) across the five selected cities in 2012. Although the mean maximum temperature is different in these five cities, it is highly correlated (with the lowest correlation coefficient \(r = 0.915\)).

Figure 5 shows the monthly mean rainfall (mm) across the five selected cities. In contrast to mean maximum temperature, the monthly rainfall has a different pattern across the selected cities. However, it is still highly correlated, with the lowest correlation coefficient \(r = 0.468\).

Table 1 provides the descriptive statistics of the variables of interest. On average, 41 crashes involving a heavy vehicle have occurred each month. Of these,
approximately two per month were caused by a heavy vehicle defect. Concurrently, 38% of vehicles on average failed their programmed inspections and returned to an inspection center for a follow-up inspection in approximately 20 days.

FAILLVL, as described in Table 1, is the monthly average of inspection failure severity levels, considering vehicles that have failed an inspection with any of the following failure severity levels:

- **Self-clearing** (level 1)
- **Minor**—no label affixed (level 2)
- **Major**—label affixed (level 3)
- **Dangerous**—label affixed (level 4)

**Time Series Analysis**

Time series analysis was used in this study to address the proposed research objective. Initially both programmed inspection results and crashes were investigated using an exploratory approach to reveal potential trends, seasonal components, and irregularities. Then, a regression model was fitted to the time series data to identify cross-
correlations and any potential impact of programmed inspections on crashes.

To reveal a potential relationship between programmed inspections and the total number of heavy vehicle crashes, a regression model was fitted to the time series data. However, the results of the exploratory analyses showed that the crash time series was not stationary, and thus the residuals of a generalized linear model fitted to the data were correlated. Figure 6 shows the partial auto-correlation function (PACF) plot for the residuals of a generalized linear model fitted to crash time series, assuming a Poisson distribution. Both PACF diagnostics (shown in Figure 6) and the Akaike information criterion (AIC) values for AR(p) models on crash time series data (shown in Figure 7) indicate that an AR(1) process can mitigate the effect of serial correlation.

An ARIMA model with first-order autoregressive disturbance (AR(p = 1)) was fitted to the heavy vehicle crash time series data. Accordingly, each observation (Xt, i.e., the total number of crashes in each month) was estimated through a linear function of p previous observations, a constant term, and a disturbance term, as follows (25):

\[ X_t = k_1X_{t-1} + k_2X_{t-2} + \ldots + k_pX_{t-p} + \theta_0 + \epsilon_t = \theta_0 + \epsilon_t \]

where
\[ X_t, X_{t-1}, \ldots, X_{t-p} \] were the observations at \( t, t-1, \ldots, t-p \),
\( p \) is the lag,
\( k_i \) are the autoregressive parameters,
\( \theta_0 \) is the constant term, and
\( \epsilon_t \) is the disturbance term at \( t \).

Given that the crash process was stationary, the mean of observations (\( X_t \)) can be calculated as

\[ E(X_t) = \frac{\theta_0}{1 - k_1 - k_2 - \ldots - k_p} \]

and its variance can be calculated as

\[ \text{VAR}(x_t) = \frac{\sigma^2_a}{1 - k_1p_1 - k_2p_2 - \ldots - k_p\rho_p} \]

where \( \sigma^2_a \) is the variance of the disturbance term. The autocorrelation coefficient was calculated using

\[ \rho_\kappa = k_1p_{\kappa-1} + k_2p_{\kappa-2} + \ldots + k_p\rho_{\kappa-p} \]

Given \( p = 1 \), as an AR(1) model was fitted to heavy vehicle crash time series data, Equation 1 becomes

\[ X_t = k_1X_{t-1} + \theta_0 + \epsilon_t \]

which implies \( |k_1| < 1 \) (for a stationary process), and the partial correlation coefficients \( \phi_{11} = \rho_1 \) and \( \phi_{\kappa\kappa} = \rho_1 \) for \( \kappa > 1 \).

Results and Discussion

As illustrated in Table 2, an ARIMA model with \( p = 1 \) was fitted to the crash time series data. The “Applied Statistical Time Series Analysis (astsa)” package (26) with R (27) were used in RStudio to run the analysis. The
The logarithm of the total number of heavy vehicle crashes in each month (LOGCRASH) was used as the dependent variable. The external regressors include TIME, FAILRATE, FAILINT, VHCLAGE, MAXTEMP, and RAINFALL. Separate models for single-vehicle and multi-vehicle crashes were also fitted for further evaluation; the results, presented in the Appendix, were very similar to the model fitted to all data.

Table 1 presents a summary of the model results. As shown in Table 2, the intercept has a positive, significant correlation with the total number of crashes ($b = 686.592$, $p = 0$). Given the complexity and diversity of factors contributing to a vehicle crash, this intercept accounts for the effects that are not captured by the other variables.

The model diagnostic plots (Figure 8) confirm the suitability of the applied model. The residuals are normally distributed, they are not highly correlated, and their auto-correlation function (ACF) and PACF fall within the acceptable thresholds; thus, the residuals do not violate the assumption of whiteness (28). The model log likelihood $= -1.087$ and the AR(1) parameter estimate $= 0.392$ is significant ($p = 0.009$).
As shown in Table 2, TIME has a significant, negative correlation with the total number of crashes ($\beta = -0.342, p = 0$). This can be attributed to a decline in total number of heavy vehicle crashes over the period of study, as shown in Figure 9.

Both FAILRATE and FAILLVL have significant, positive correlations (at $\alpha = 0.1$) with the total number of crashes ($\beta = 5.306, p = 0.058$ and $\beta = 1.778, p = 0.086$, respectively). Given a one-month lag considered in the model for the inspection results, both FAILRATE and FAILLVL indicate the extent of technical issues of the heavy vehicles driven after inspections. A higher value of FAILRATE means that more heavy vehicles with technical deficiencies will be on roads, while a higher value of FAILLVL indicates that defective vehicles with more severe technical problems will be driven.

Although the effect size of these inspection-related variables is relatively small (because of the small correlations between inspection outcomes and road safety measures), it is still important to consider such potential effects, as any changes in the road safety measures involves people’s lives. These results specifically show that the overall programmed inspection outcomes across the state, in relation to the monthly average inspection failure rate —FAILRATE— and the monthly average inspection failure severity level —FAILLVL— can be used as predictors of the total number of heavy vehicle crashes in the month following the inspection.
MAXTEMP has a significant negative correlation with the total number of crashes ($\beta = -0.036, p = 0.019$). Figure 10 illustrates this negative association as well as the seasonal trends of the number of heavy vehicle crashes and the average mean maximum temperature over one year. One potential explanation for such a negative association is that there were fewer heavy vehicles on roads when the weather was very hot, and thus there was a lower chance of heavy vehicle crashes in such conditions. However, fine-grained data were not available to validate this explanation. The most reliable sources of information on the use of motor vehicles in Australia are the Australian Bureau of Statistics (12) and the Australian Department of Infrastructure and Regional Development (13). These sources collect and publish their data on an annual basis.

Finally, FAILINT, VHCLAGE, and RAINFALL did not show a significant correlation with the total number of crashes, as indicated in Table 2. Both FAILINT and VHCLAGE are related to the quality of heavy vehicles. Given the small percentage of crashes caused by a vehicle defect (3.69% over the period of study), and the indirect correlation between FAILINT as well as VHCLAGE, and vehicle road-worthiness, the analysis results do not show a significant effect of these two variables on the total number of heavy vehicle crashes. The non-significant correlation between RAINFALL and the total number of heavy vehicle crashes can be attributed to the use of an aggregated measure for rainfall across the state, where patterns vary among climate zones, as explained in the Method section.

To investigate the potential relationship between heavy vehicle programmed inspections and crashes caused by a defect, a regression model was fitted to the time series data. The defect-related crash time series was stationary, and thus there is no need to apply an ARIMA model, as the residuals of a generalized linear model fitted to the data would not be correlated. Figure 11 shows the PACF plot for the residuals of a generalized linear model fitted to the defect-related crash time series data. Both PACF diagnostics (shown in Figure 11) and Durbin-Watson Statistic ($DW = 2.23, p - value = 0.64$) indicate that the defect-related crash time series was stationary, and the residuals of the linear model fitted to the data were not correlated.

Table 3 summarizes the results of the generalized linear model fitted to the defect-related crash time series data. The number of heavy vehicle crashes caused by a

| Estimate | Standard error | $t$ value | Pr($>|t|)$ |
|----------|----------------|-----------|-----------|
| Intercept  | 358.652        | 324.129   | 1.107     | 0.275     |
| TIME      | -0.173         | 0.162     | -1.067    | 0.292     |
| FAILRATE  | 34.139         | 15.092    | -2.262    | 0.029     |
| FAILHIGH  | -1.451         | 5.323     | -0.273    | 0.786     |
| FAILINT   | 0.016          | 0.093     | 0.169     | 0.867     |
| VHCLAGE   | -0.908         | 0.421     | -2.157    | 0.037     |
| MAXTEMP   | 0.152          | 0.058     | 2.614     | 0.012     |
| RAINFALL  | 0.000          | 0.002     | 0.074     | 0.942     |
| FAILRATE X FAILHIGH | -1004.944 | 446.829   | -2.249    | 0.030     |
| FAILRATE X FAILINT   | 16.166        | 7.357     | 2.197     | 0.033     |

Note: (Pr > $|t|$) = two-tailed $p$ - value.
heavy vehicle defect in each month (DFCTCRSH) was used as the dependent variable. The model’s independent variables include: TIME, FAILRATE, FAILHIGH, FAILINT, VHCLAGE, MAXTEMP, and RAINFALL. The interaction effects between FAILRATE and FAILHIGH as well as FAILRATE and FAILINT were also considered. Similar to the approach used for modeling the total number of heavy vehicle crashes, separate models were fitted to the data on heavy vehicle crashes caused by a heavy vehicle defect considering only single-vehicle versus multi-vehicle crashes. The results, which show very similar patterns in the three models (all data, single-vehicle crashes and multi-vehicle crashes), are presented in the Appendix.

As shown in Table 3, neither the intercept nor TIME were significant predictors of the number of defect-related crashes. This was potentially because of the low number of such crashes (between zero and six crashes monthly, as shown in Table 1). The number of defect-related crashes, however, varied over time. Although it had an overall declining trend until mid-2012, an ascending trend was observed afterwards (shown in Figure 12).

Among the three variables related to programmed inspection outcomes (i.e., FAILRATE, FAILHIGH, and FAILINT), only FAILRATE had a significant, positive association with the number of defect-related crashes ($\beta = 34.139, p = 0.029$). As no time lag was considered in this model, FAILRATE indicates the technical soundness of heavy vehicles in each month, and thus it was a true predictor of the number of defect-related crashes in the same month. The similar trend of FAILRATE and DFCTCRSH over the period of study (shown in Figure 12) also confirms this finding. The non-significant associations between FAILHIGH and DFCTCRSH as well as FAILINT and DFCTCRSH can be attributed to the very low number of defect-related crashes and the resulting low statistical power.

VHCLAGE as the only vehicle related attribute considered in the model also had a significant, but negative relationship with DFCTCRSH ($\beta = -0.908, p = 0.037$). One possible explanation is that the drivers of older heavy vehicles drove more carefully and were therefore less likely to cause crashes.

Of the weather-related variables, MAXTEMP had a significant, positive relationship with DFCTCRSH ($\beta = 0.152, p = 0.012$), while RAINFALL did not have a significant relationship. The positive relationship of MAXTEMP can be attributed to hot weather and its negative implications on driver behavior which could be compounded by vehicle defects. The non-significant correlation between RAINFALL and DFCTCRSH may be because of the intrinsic inaccuracy of the aggregated measure of rainfall used in this study, as explained earlier.

The preceding finding is especially interesting when considering the interaction effects between FAILRATE and FAILHIGH ($\beta = -1004.944, p = 0.03$) as well as FAILRATE and FAILINT ($\beta = 16.166, p = 0.033$). Given the significant, positive relationship between FAILRATE and the number of defect-related crashes, the significant, negative interaction between FAILRATE and FAILHIGH indicates a suppressive effect of FAILHIGH on the positive correlation between FAILRATE and DFCTCRSH. This may be because highly defective vehicles, as identified in programmed inspections, will be absent from roads. Thus, having a larger number of vehicles with high or dangerous failure levels decreases the effect of a high average inspection failure rate on the number of defect-related crashes.

By contrast, the significant, positive interaction between FAILRATE and FAILINT indicates the synergistic, positive correlations of the two variables with DFCTCRSH. This result can be attributed to a higher FAILINT, meaning that defective heavy vehicles were on roads for a longer period of time before their defects were fixed and reinspected. This had a significant effect on the number of defect-related crashes when there were more defective vehicles on roads, as indicated by a high FAILRATE.

Conclusions

This study analyzed relationships between the outcomes of programmed heavy vehicles inspections and relevant crash time series data from Queensland, Australia, for the period June 2009 through December 2013. This study has not investigated potential causal effects of programmed heavy vehicle inspections on the road safety because of a lack of access to fine-grained data as well as practical complexities of such an investigation. The analysis results showed that the total number of heavy vehicle crashes is correlated with the monthly average inspection
failure rate as well as the monthly average failure severity level. Moreover, the study showed a significant correlation between the number of defect-related crashes and the monthly average inspection failure rate, the average vehicles’ age, and the monthly average mean maximum temperature. These significant correlations can inform development and adjustment of precautionary measures which in turn could enhance the overall safety of heavy vehicles on roads, as summarized next.

First, it is recommended that traffic safety agencies pay more attention to the results of programmed heavy vehicle inspections; they are more likely to have defect-related and other types of heavy vehicle crashes in the subsequent months, if the monthly average failure inspection rate rises in a given month. There average inspection failure rate can be used as a measure to forecast future road safety. This rate reflects the current technical state of heavy vehicles. A potential implication for traffic safety agencies is to consider more serious and timely follow-up inspections when heavy vehicles fail their programmed inspections. This is especially important, as longer intervals between failed inspections and their follow-up inspections intensify the adverse effect of a high monthly average failure rate for defect-related crashes.

Second, the average failure severity level of all inspections during a month has a significant positive correlation with the total number of heavy vehicle crashes during the subsequent month. This finding potentially indicates that the severity of failures identified through programmed inspections is also an indicator of the overall technical condition of the inspected heavy vehicles. A high monthly average failure severity level reflects many severe problems associated with the inspected heavy vehicles, which in turn increases the likelihood of crashes in the near future. Road safety policies need to be updated accordingly, specifically to inhibit heavy vehicles with severe inspection failures from being driven before obtaining a clearance in a follow-up inspection.

Third, the average mean maximum temperature has a significant negative and positive correlation with the total number of heavy vehicle crashes and the number of defect-related crashes, respectively. As previously discussed, it is feasible that fewer heavy vehicle kilometers are driven in hot weather, which in turn lowers the likelihood of heavy vehicle crashes. Hot weather conditions, however, may increase the likelihood of heavy vehicle defects and the associated crashes. As a precautionary policy, further training and guidelines can be provided to drivers of heavy vehicles for driving during extreme weather conditions. The provision of relevant informative booklets and vehicle safety checklists can also assist drivers to enhance safety during hot weather conditions.

This study has limitations. First, the data used for the time series analyses were limited in both measured variables and period of observations because of access agreements. This study has therefore focused on several aspects of periodic heavy vehicle inspections considering the characteristics of the available data. Second, the data included a variety of heavy vehicles from buses to trucks, while COI-exempt vehicles were not considered in the analysis. Along with the limited set of observed variables, this limitation can increase the potential effect of unobserved heterogeneity. Finally, this study has considered two abstract measures of weather conditions as potential external factors contributing to heavy vehicle crashes. Considering accurate and detailed measures of weather conditions along with other well-established crash contributing factors (e.g., light condition and road surface condition) is likely to contribute to the analysis of programmed inspections and their relationship with heavy vehicle crashes.

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The authors confirm contribution to the paper as follows: study conception and design: B. Assemi; data collection: B. Assemi, M. Hickman; analysis and interpretation of results: B. Assemi, M. Hickman; draft manuscript preparation: B. Assemi, M. Hickman, A. Paz. All authors reviewed the results and approved the final version of the manuscript.

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