IDEA

Innovations Deserving
Exploratory Analysis Programs

Transit IDEA Program

Evaluation of an Automatic, Individual Computer-Based Driver Education and Training Program

Final Report for
Transit IDEA Project 88

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Transportation Research Board
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Washington, DC 20001

Evaluation of an Automatic, Individual Computer-Based Driver Education and Training Program

IDEA Program Final Report

For the period *January 2018* through *March 2021*

Transit-88

Prepared for the IDEA Program

Transportation Research Board

National Academies of Sciences, Engineering, and Medicine

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    - Jeffrey Hickman, Group Leader and Research Scientist
    - Susan Soccolich, Statistician
- RMJ Technologies and Predictive Coach
    - Jerome Toliver, Chief Executive Officer
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Glossary

The contractor should include a glossary, if necessary, to define technical terms.

CI	confidence interval
CTBS	Center for Truck and Bus Safety
ID	identification
IDEA	Innovations Desearving Exploratory Analysis
OSM	onboard safety monitoring
RR	risk ratio
TCRP	Transit Cooperative Research Program
TRID	Transportation Research International Doccumation
VTTI	Virginia Tech Transportation Institute

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Investigator Profile

Matthew Camden is a Senior Research Associate in the Virginia Tech Transportation Institute's (VTTI's) Center for Truck and Bus Safety (CTBS), Behavioral Analysis and Applications group. He is an occupational driving safety expert with more than 14 years of experience conducting applied driving research and translating that research to industry practice. Mr. Camden specializes in light-vehicle and heavy-vehicle fleet safety with an emphasis on developing and evaluating occupational safety programs and advanced vehicle technologies to improve driver performance. His research portfolio includes the evaluation of advanced vehicle safety systems, organizational safety culture, driver distraction and fatigue, driver training, and driver impairment. Mr. Camden also leads CTBS's driver training/education and public outreach efforts related CMV driver performance and sharing the road with trucks. He has been the PI/Co-PI or Project Manager on 29 projects totaling over $4.4 million and has made significant contributions to 16 other projects (totaling over $16.6 million). These projects include federally and privately funded research projects from the National Safety Council, Federal Motor Carrier Safety Administration, National Academy of Science, National Highway Traffic Safety Administration, AAA Foundation for Traffic Safety, Transport Canada, North American Fatigue Management Program, Clear Roads, National Transportation Research Center, Inc., and National Surface Transportation Safety Center for Excellence. Mr. Camden has over 75 professional presentations and more than 50 scientific publications and technical reports.

Executive Summary

Driver behavior is the primary contributing factor in the majority of crashes (*1-3*). Thus, safety technologies and programs aimed at reducing or eliminating risky driving behaviors may prevent a large number of crashes. One technology that has been found effective at reducing risky behaviors is an onboard safety monitoring (OSM) system (*4-9*). OSM systems incorporate in-vehicle recording technology that continuously measures and records the driver's performance. However, data suggest that OSM systems alone are insufficient to create lasting behavioral change. Instead, lasting behavioral change results from using the data from OSM systems to offer individualized driver coaching/training.

Innovations Deserving Exploratory Analysis (IDEA) Product

Predictive Coach uses kinematic-based OSM devices to monitor instances of risky driving, which are subsequently communicated to the back-office software and assigned to the driver in the vehicle (Figure 1). Once the maximum number of risky driving behaviors specified by the end-user fleet is reached, Predictive Coach automatically assigns driver training tailored specifically to address the risky behavior identified for that driver. The driver has one week to complete the self-paced training course. After completion, the results are automatically transmitted back to Predictive Coach and the OSM system for tracking and manager follow-up (if needed). Finally, the course results, along with driver identification, risky driving thresholds, and behavioral trends, are made available via the OSM system dashboard and reports.

Figure 1. Overview of the Predictive Coach Program

Results

Results showed the bus drivers had 7,267 risky driving events over the 34 weeks, including 0 hard acceleration events, 39 hard braking events, 5,786 hard cornering events, and 1,442 excessive speeding events while operating the buses. Figure 2 shows the weekly average of bus operators' risky driving events per 1,000 miles.

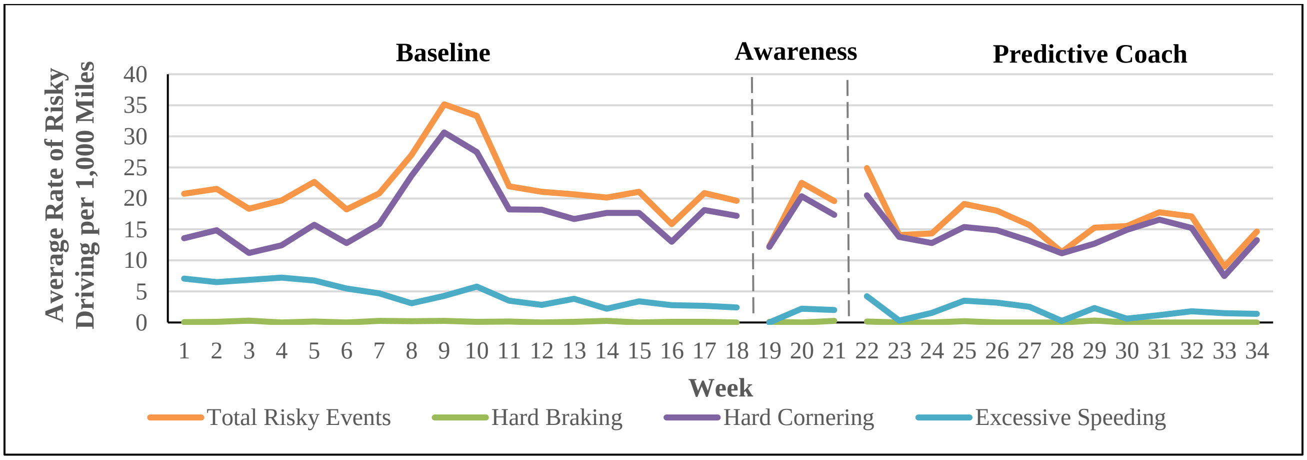

Figure 2. Average Rate of Bus Drivers' Risky Driving Events per 1,000 Miles per Week Across All Bus Drivers.

Table 1 shows the rates of overall risky behavior, excessive speeding, and hard cornering were found to be significantly lower during the Predictive Coach phase compared to the Baseline Phase.

Table 1. Results comparing specific risky driving behavior rates in each study phase for bus drivers.

Risky Driving Type	**Comparison**	**RR Estimate**	**Adj CI**	***df***	***t*-value**	***p*-value**
Overall	Predictive Coach vs. Baseline	0.6940*	(0.6527, 0.7568)	578	-9.37	<.0001
Excessive Speeding	Predictive Coach vs. Baseline	0.3662*	(0.3002, 0.4469)	578	-9.91	<.0001
Hard Cornering	Predictive Coach vs. Baseline	0.8104*	(0.7478, 0.8783)	578	-5.14	<.0001

Conclusions

Results from this study showed that the Predictive Coach program was associated with a reduction in bus drivers' risky driving behaviors, including a 63% reducing in excessive speeding events. It offers fleets an objective method of identifying drivers in need of training, offers targeted training courses based on individual driving habits, and does all of this automatically without the need for fleet intervention. Additionally, the results showed that Predictive Coach program provides a complimentary system to video-telematics OSM systems to help fleets further reduce risky driving.

IDEA Product

Risky driving behaviors (e.g., speeding, close following distances, and aggressive driving) and driver error (e.g., unplanned lane deviations, lateral encroachment, and failure to yield) are the primary contributing factors in the vast majority of vehicle crashes (*1-3*). Thus, safety technologies and programs aimed at reducing risky driving behaviors and driver errors may lead to large crash reductions. One technology that has been found effective to reduce risky behaviors is an onboard safety monitoring (OSM) system. OSM systems incorporate in-vehicle recording technology that continuously measures and records the driver's performance. Although several studies have found OSM devices to be highly effective at increasing driver safety (*4-9*), some data suggest that the use of OSM systems alone is insufficient to significantly reduce risky driving behaviors in the long term (*5,9*). Instead, lasting behavioral change results from using the data from OSM systems to offer individualized driver coaching/training.

Although using OSM data to create individualized coaching/training is effective, it is a time-consuming process. Fleets are required to monitor each driver's OSM data, identify behavioral trends, and meet with drivers to review OSM data and offer individualized feedback and coaching. As a result, fleets may not offer the individualized training on a regular or consistent basis.

Predictive Coach Product

To address this challenge, RMJ Technologies developed Predictive Coach, a first-of-its kind software program that uses OSM system data to monitor driver behavior and automatically assign relevant, individualized online driver training as needed. Predictive Coach incorporates a three-step process, as shown in Figure 3. Some may not consider the use of OSM systems and driver training innovative per se; however, the evaluation of targeted training delivery, tailored training content, and automatic training tracking and documentation is an innovative concept.

Figure 3. Predictive Coach's 100-percent automated process.

First, Predictive Coach uses kinematic-based OSM devices to monitor instances of risky driving. During this study, the Geotab telematics device was used (Figure 4). The OSM system targets individual drivers and tracks their behavior. Predictive Coach uses the OSM device to record instances where the driver exceeded specific thresholds for speeding, hard braking, rapid acceleration, hard cornering, seat belt use, turn signal use, etc. In addition to tracking instances of risky driving, the OSM device provides a real-time alert to the driver any time the threshold is exceeded. The thresholds are established by the end-user fleet. Instances where the driver exceeded the thresholds established for safe driving are communicated to the back-office software and assigned to the driver in the vehicle.

Figure 4. Geotab Go9 telematics device.

Table 2 shows the risky driving thresholds used in this study. The risky behaviors targeted in this study included hard acceleration, hard braking, hard cornering, and speeding. These thresholds were selected based on Geotab's previous experience identifying risky driving and in coordination with the participating carrier.

Table 2. Risky Behavior Thresholds

Behavior	Bus Threshold	Light-Vehicle Threshold
Rapid Acceleration	Peak acceleration > 0.29 g Duration of acceleration exceeding threshold between 2 seconds and 2 minutes Distance travel while acceleration exceeded threshold > 10 yards	Peak Acceleration > 0.36 g Duration of acceleration exceeding threshold between 2 seconds and 2 minutes Distance travel while acceleration exceeded threshold > 10 yards
Hard Braking	Peak Deceleration > −0.47 g Speed > 5 mph Distance travel while deceleration exceeded threshold > 2 yards	Peak Deceleration > −0.61 g Speed > 5 mph Distance travel while deceleration exceeded threshold > 2 yards
Hard Cornering	Lateral acceleration/deceleration > │0.32 g│ Speed > 10 mph Lateral acceleration/deceleration < 10 seconds Lateral acceleration/deceleration > 1.5 yards	Lateral acceleration/deceleration > │0.40 g│ Speed > 10 mph Lateral acceleration/deceleration < 10 seconds Lateral acceleration/deceleration > 1.5 yards
Speeding	Speeds > 10 mph over the posted speed limit Speed maintained for more than 20 seconds	Speeds > 10 mph over the posted speed limit Speed maintained for more than 20 seconds

Once the maximum number of risky driving behaviors specified by the end-user fleet was reached, Predictive Coach automatically assigned driver training tailored to address the risky behavior identified for that driver. For example, if a driver exceeded a specified hard-braking threshold 15 times, the driver was issued a training module designed to improve braking performance. Once the training was assigned, the driver and the driver's manager received an instant notification. Once the driver completed the self-paced training course, the results were automatically transmitted back to Predictive Coach and the OSM system for tracking and manager follow-up (if needed). Finally, the course results, along with driver identification, risky driving thresholds, and behavioral trends, were available via the OSM system dashboard and reports. If the initial training intervention did not result in behavioral change, the process repeated with a longer training course which combined several of the training modules. Figure 5 shows the five-step method for training: 1) identify which training is needed, 2) notify driver and manager of assignment, 3) the driver completes traing, 4) the training results are uploaded to the Predictive Coach system, and 5) managers can access results via the Predictive Coach dashboard.

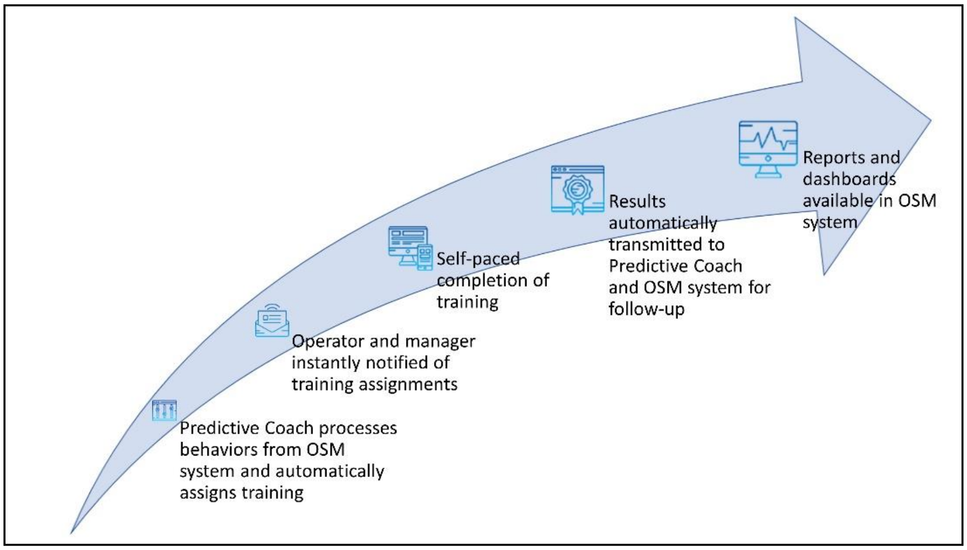

Figure 5. Predictive Coach training process.

Each initial training course was designed to be 3- to 5-minutes long and included audio narration, a written narration transcript, and visually stimulating graphics and video. Within each 3- to 5-minute training course were two or more interactive knowledge checks. Follow-up training (if needed) was more comprehensive and was designed to be 20 to 30 minutes long. A total of 25 initial training courses were available. Table 3 reports the training courses that targeted each of the four risky driving behaviors. Drivers were assigned Training Assignment 1 the first time they exceeded the maximum number of risky driving behaviors. Drivers were assigned the next course down the list each subsequent time the maximum number of risky driving behaviors was exceeded.

Table 3. Training Courses per Risky Behavior

	Hard Braking	**Hard Acceleration**	**Hard Cornering**	**Speeding**
Training Assignment 1	Inattention & distraction	Aggressive driving	Turning	Risk management
Training Assignment 2	Covering the brakes	Passing	Scanning	Emotions

Training Assignment 3	SMART approach	Road hazards	Types of intersections	Collision prevention
Training Assignment 4	Right of way	Changing lanes	Weather	Stress
Training Assignment 5	Managing risk	Managing risk	Signs & signals	Driver readiness
Training Assignment 6	Basic vehicle maneuvers	Driver readiness	External risk factors	Collision prevention 2
Training Assignment 7	-	-	-	Risk perceptions
Training Assignment 8	-	-	-	Managing risk
Training Assignment 9	-	-	-	Aggressive driving
Training Assignment 10	-	-	-	External risk factors

Concept and Innovation

This method of targeted training for individual drivers was different from traditional training, in which all drivers receive the same training, regardless of whether it is relevant to the driver. The method used in the Predictive Coach concept was desgined to be more efficient and enhance knowledge retention. The innovative method of delivering training ensured that drivers and fleets were not spending excess time and money on training in areas that were not justified by behavioral data for particular drivers. In addition to enhancing driver safety, the targeted training enhanced fleet efficiency and reduced cost as the targeted behaviors affect fuel use, vehicle maintenance, and insurance expenses. Instead of paying drivers a full hour or day to complete training that they may not need, the Predictive Coach system only requires drivers to spend approximately 5 minutes to review only the concepts they need. Additionally, reducing hard braking, hard acceleration, hard cornering, and speeding improve fuel efficient driving, thus saving the fleet fuel costs. Finally, by reducing risky driving, fleets can prevent crashes, and thus, reduce insurance costs and crash costs.

Summary of Prior Work

The research team conducted a literature review of automated, online, driver-specific training systems in bus transit operations. This review included the Transportation Research Board's Transport Research International Documentation (TRID) database and the completed and ongoing projects listed on the Innovations Deserving Exploratory Analysis (IDEA) website. To identify relevant published research in the TRID database, the following search terms were used: transit AND coaching, transit AND driver training, transit AND driver training, transit AND driver education, transit AND driver education, transit AND onboard monitoring, transit AND aggressive driving, and transit AND defensive driving. This search resulted in 345 potentially relevant citations. Of these 345 citations, 178 citations were from work published before 2000 (it is unlikely that pre-2000 OSM technology automatically assigned and tracked driver-specific training), nine were duplicates, and 132 were not relevant based on a review of the article's title and abstract. Thus, a total of 26 articles were subjected to a full review to identify their relevance to the proposed training concept. Only three of those 26 articles discussed Web-based driver training or driver training based on data from an OSM system (*9-12*), however, none of the articles reviewed included Web-based driver training based on data from an OSM system.

Nicholson et al. identified the potential of e-learning to meet the needs of the transit industry related to operating training and outlined several e-learning courses (*9*). However, none of these courses used data from an OSM device to tailor training or target individual drivers. Haynes conducted a case study with two bus transit fleets in Australia; these fleets used data from OSMs to inform face-to-face driver training but did not use the data to provide individually tailored training (*10*). When assessing best practices related to transit driver training, Staes et al. found that 49% of the surveyed fleets used an OSM system, 29% of respondents used some form of online training (*11*). Although this study discussed the potential of individualized driver training/coaching based on OSM system data, no fleets were equipped with systems that automatically identified and assigned online training based on the OSM data.

The review of ongoing and completed Transit IDEA and Transit Cooperative Research Program (TCRP) projects revealed three projects related to online training (*12-14*). However, these projects were substantially different from the proposed concept. In Transit IDEA project 13, Mesnick developed a computer-based, interactive training course designed to enhance the training of rail workers in track maintenance and construction (*12*). This project focused only on track maintenance personnel and was not related to driver training. Furthermore, it was unrelated to the innovative training-delivery concept in the current proposal. Transit IDEA project 62 also developed an online training course for bus transit maintenance technicians (*13*). This course was designed to improve technicians' knowledge of vehicle electrical systems. Similar to the previous project, transit drivers were not the target audience for the training, and the project did not entail an innovative training-delivery concept as in the current proposal. Finally, the TCRP has an ongoing study documenting best practices and barriers in implementing innovative training programs for transit drivers and maintenance personnel (*14*). Although the results of this TCRP study may be useful when implementing the proposed driver training, the proposed concept is not similar to the proposed work.

The lack of prior research investigating online, individually tailored training based on OSM system data highlights the need for the creation and evaluation of innovative training solutions targeting transit drivers. Furthermore, the work by Staes et al. indicated that OSM systems and online training are prevalent in the transit industry (*11*). Thus, the proposed training method will be well-positioned to gain user acceptance and be quickly implemented in existing fleets.

Investigation

This project is a concept exploration designed to evaluate the ability of Predictive Coach's innovative driver training delivery method to reduce risky driving behavior. This study evaluated three research questions:

1. What are the safety benefits (i.e., reduction in frequency of risky driving behaviors) of Predictive Coach?
2. Are there any unintended side effects associated with the use of Predictive Coach?
3. What are managers' and drivers' perceptions and opinions of the automated training?
4. Does Predictive Coach have potential use in the transit industry?

The original plan to evaluate the effectiveness of the Predictive Coach program was to equip 30 vehicles at a large transit fleet in the southeast. However, this fleet was ultimately unable to participate in the project due to numerous other large-scale projects that occurred during the project's timeline, the need for drivers to carry an identification fob to track their specific beahvior, and difficulty getting buy-in from driver managers. Following this decision, RMJ Technologies and the research team began to search for a replacement transit agency in June 2018. Of the four transit agencies that were contacted about possible participation, one large transit agency in the southwestern United States agreed to participate. The research team received a formal written letter of commitment from Fleet A on August 14, 2018. Baseline data collection began on March 6, 2019; however, on August 7, 2019, the fleet informed the research team that they would ultimately be unable to participate. The project champion received significant pushback about implementing the Predictive Coach program.

Thus, the research team was required to find a second replacement fleet to participate in the program. On September 10, 2019, VTTI initiated discussions with Keolis North America to discuss participation. The Vice President of Safety at Keolis North America agreed to participate based on approval from their legal department. On September 30, 2019, VTTI received official approval from Keolis North America to participate in the project at one of their non-union locations in Florida.

Participating Fleet

Keolis is an international private transit fleet with over 63,000 employees across the world, including dozens of locations across the U.S. and Canada. Keolis has long valued passenger and driver safety, including through the use of advanced technologies and industry best practices related to driver training. Keolis offers bus, rapid transit, tram, rail, motor coach, and taxi services, including at many of the locations across the U.S. As mentioned above, this study took place at a Keolis terminal in Florida.

As part of Keolis' commitment to bus driver safety, the Florida location used Lytx®'s DriveCam® program. The DriveCam® program uses in-cab video cameras and accelerometers to collect driving behavior data. Based on these data, Keolis managers coached drivers on their risky driving. Keolis found success with the DriveCam® program, reducing their near-crashes and crashes. Additionally, the site safety manager at the participating Keolis' Florida location was voted DriveCam®'s Coach of the year. Thus, this Keolis terminal was already a safe fleet. However, the idea of automated driver trainings, in addition to the DriveCam® program, was of interest to Keolis.

On the weekend of December 7, 2019, RMJ Technologies installed the Geotab devices in all 30 vehicles. Of these vehicles, 26 were transit buses (see Figure 6) and four were light-vehicles (see Figure 7); however, one of the light vehicles was not driven during the study. The buses operated normal routes transporting passengers to their destinations. The light-vehicles were used to transport drivers, technicians, and managers to different terminals. The same drivers operated both the buses and the light vehicles. The installation process went smoothly, and the research team confirmed the Geotab devices were recording the required data. As Keolis uses a slip seat operation, each driver may operate any of the vehicles. Thus, each driver needed to scan an identification key fob at the start of the shift. This required additional driver training which took place between December 23, 2019 and January 21, 2020. A total of 59 drivers participated in this pilot for at least 1 week.

Figure 6. Keolis bus similar to the ones used in this study.

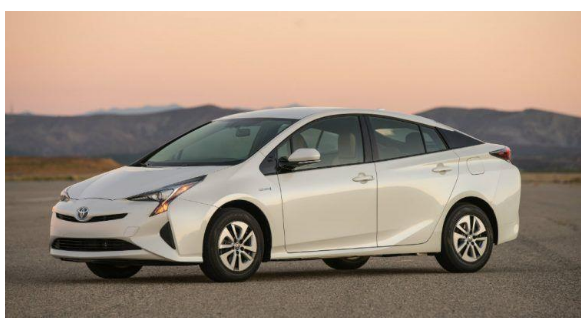

Figure 7. Keolis light vehicle similar to the ones used in this study.

Study Methogology

Data were collected over 34 weeks. Figure 8 displays a timeline for the data collection, including three separate phases.

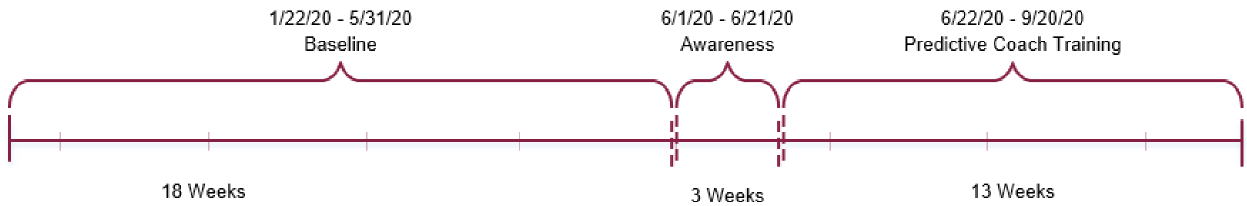

Figure 8. Study Timeline.

As shown above, baseline data collection occurred for 18 weeks between January 22, 2020 and May 31, 2020. Between June 1, 2020, and June 21, 2020, the onsite safety manager conducted in-person driver awareness and training on the Predictive Coach program. This included an overview of the program, how training was assigned, and how to complete training. Finally, three months of Predictive Coach driver training data collection occurred between June 22, 2020, and September 20, 2020. Although Geotab devices were installed on four light-vehicles, and driving data were collected, the assignment of Predictive Coach trainings was not contingent on driving behavior in the light vehicles. Furthermore, driver IDs were not collected during light vehicle trips. Thus, drivers could only be assigned a Predictive Coach training based on how they performed while driving a bus. However, data collected from the light vehicles were used to assess if there were any unintended consequences of the Predictive Coach program (i.e., did the drivers' behavior change while driving the light vehicles).

The Keolis fleet were instructed to continue with their normal operating procedures for the duration of the study with one exception: the fleet was instructed to follow Predictive Coach training procedures starting on June 22, 2020. No other requirements or instructions were given to the fleet. During the driver training phase RMJ Technologies monitored training assignments and completion to ensure that the program was working as intended. VTTI monitored the driver behavior data to ensure that all required data were being recorded.

After three months of Predictive Coach data collection, RMJ Technologies personnel returned to the fleet site to uninstall the Geotab devices. Additionally, VTTI researchers collected qualitative data via two questionnaires. The first questionnaire targeted managers at the fleet. The second questionnaire targeted drivers. These questionnaires gathered managers' and drivers' opinions and perceptions of Predictive Coach. Topics covered in the questionnaires included (1) the effectiveness of Predictive Coach in improving driver safety; (2) the benefits and disadvantages of using Predictive Coach; (3) desired changes that may improve the training process; (4) the relevancy and engagement of Predictive Coach; (5) potential barriers to implementing Predictive Coach; and (6) opinions on recommending Predictive Coach to other bus transit fleets.

Analysis

To assess the impact study phase had on rates of risky driving behaviors, Poisson mixed-effect regression models were used. Poisson regression is a technique often used in assessing frequency of driving behaviors by another variable of interest (*15*). The risky driving behavior data included a behavior type (description) with vehicle identification (ID), driver ID (if available), and date of occurrence. Missing driver ID information from a portion of the behavior data set impacted the decision to summarize the data by vehicle ID. Calculations of total risky driving behaviors per week, per vehicle, were labeled with the corresponding study phase. The behavior data was joined to mileage data, which was also summarized by vehicle and week. A review of the calculated risky driving behavior rates revealed study weeks 9 and 10 were associated with a large increase in risky driving rates (see Figure 10 below). During these weeks in the study, Covid-19 lock downs and travel restrictions first went into effect across the data collection area. This resulted in significant interruptions to normal transit business operations at the Keolis' Florida location. As a result, all administrative work was moved off site and there was a 40% reduction in service. Due to the potential for confounding effects of the initial Covid-19 lock downs, weeks 9 and 10 were not included in the analysis. Within the light vehicle data, weeks 19 and 34 also showed outlier risky driving counts, perhaps due to some data collection issue (see Figure 15). For this reason, these weeks were excluded in the analysis of light vehicle risky driving rates.

In this study, Poisson mixed-effect models estimated how risky driving events per miles traveled (the exposure value) changed with study phase. Separate regression models were built for each risky driving event type (overall, speed, corner, brake, and acceleration events) and vehicle type (bus, light vehicle). The event counts were modeled by study phase. Although it was possible for drivers to use multiple vehicles during the study, plots of the data revealed vehicles with different and distinct risky driving event behavior patterns. This is likely evidence drivers often remained with a specific vehicle in the study (for the light vehicle data, the absence of driver ID meant the plots alone served as evidence that a mixed model approach was needed). To account for differences in exposure, weekly miles traveled was used as an offset in the model. The model was structured as follows:

$$Y_{jt} \sim Poisson(E_{jt}\lambda_{jt})$$

where Y_{jt} was the number of risky driving events for vehicle j in study phase t; E_{jt} was the total exposure in miles for vehicle j in study phase t; and λ_{jt} was the expected risky driving event rate for vehicle j in time period t.

$$\log(\lambda_{jt}) = X'_{jt}\beta + \alpha_j$$

Where $\beta$is the parameter for study phase t and X_{jt} is a vector for vehicle j and study phase t. A random effect for vehicle j is included as α_j. The risky driving event rate term $\lambda_{jt}$is linked to the model explanatory variables by a logarithm link function.

In this report, study phases are compared two at a time using risk ratios (RRs) and confidence intervals (CIs) calculated from the models. The RRs describe estimated differences in risky driving event rates for the two study phases being compared. To account for multiple comparisons in the analysis (three pairwise comparisons to compare the Baseline, Awareness, and Predictive Coach phases to each other), a Tukey adjustment was used for the comparison tests.

Results

The three study phases were compared using Poisson mixed-effect regression models that measured the impact of study phase on the rate of risky driving events per driving mile. The analysis was performed by vehicle type, using bus drivers' risky driving and mileage data and light vehicle drivers' risky driving and mileage data. Impacts of study phase on risky driving were examined for all risky driving event types together and by individual risky driving event types. Due to very low observation counts, rates of rapid acceleration were not assessed.

Overall Prevalence of Risky Behaviors

Across the 34 weeks, the bus drivers had 7,267 instances of where their driving behavior exceeded the acceptable threshold for safe driving. Of these risky driving events, there were 0 hard acceleration events (0%), 39 hard braking events (0.5%), 5,786 hard cornering events (79.6%), and 1,442 excessive speeding events (19.8%). The light vehicle drivers recorded 3,772 risky driving events across the 34 weeks. These included 1 hard acceleration event (0%), 14 hard braking events (0.4%), 406 hard cornering events (10.8%), and 3,351 excessive speeding events (88.8%).

Of the 59 drivers that participated in this study, 58 drivers recorded at least one risky driving event; the one driver that did not have any risky driving events only participated in the study for one week. However, the majority of the risky driving events were recorded by a small percentage of drivers. Figure 9 shows the percentage of total risky driving events per driver. Seven drivers accounted for approximately 50% of all risky driving events.

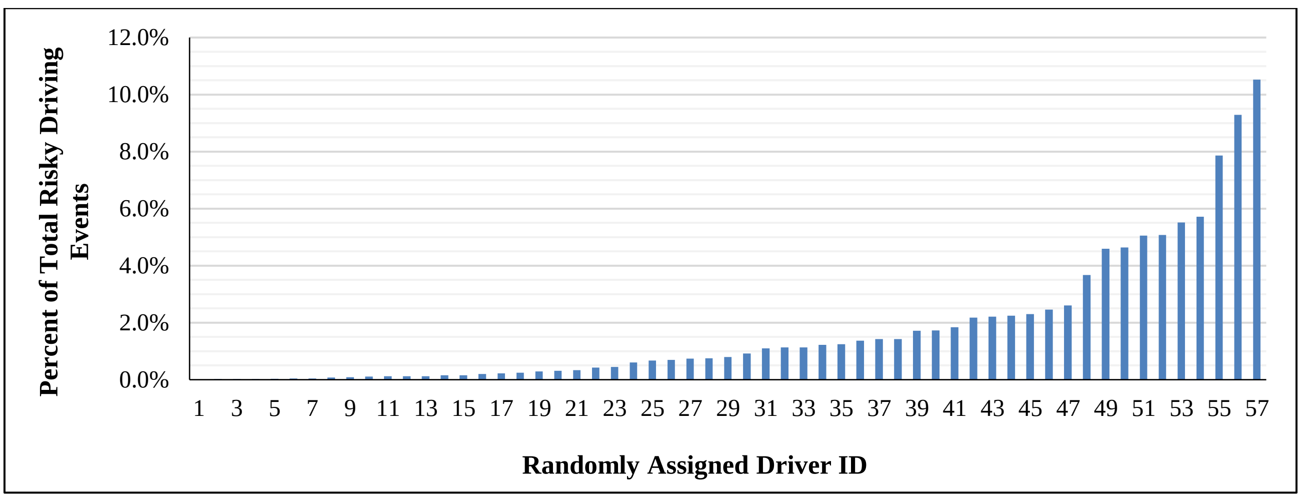

Figure 9. Percentage of Risky Driving Events per Driver.

Transit Buses

The average weekly rate of all risky driving events per 1,000 miles traveled was calculated for each study phase. The calculations used weekly risky driving counts and miles traveled for all buses. Figure 10 shows the average rate of risky driving per 1,000 miles per week across the entire study.

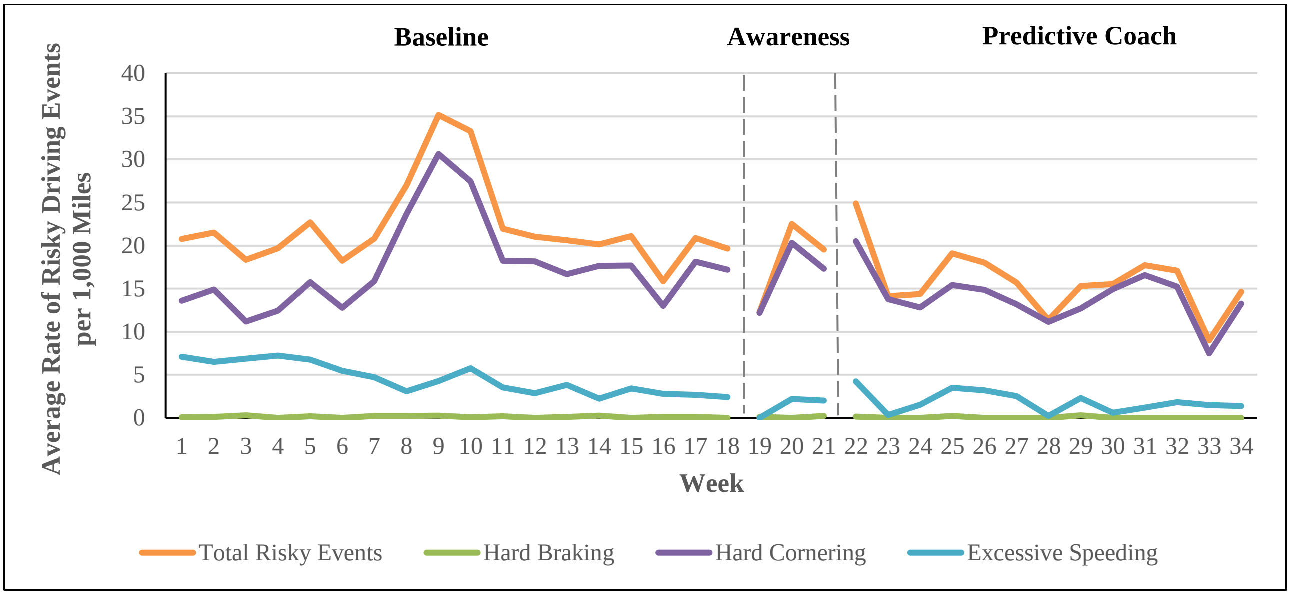

Figure 10. Average Rates of Bus Drivers' Risky Driving Per 1,000 Miles Across All Drivers.

Table 4 shows the averages for each of the risky driving behaviors. The Baseline phase had a weekly average rate of 19.31 overall risky driving events per 1,000 miles; the Awareness and Predictive Coach phases had average rate rates of 16.58 and 13.83 overall risky driving events per 1,000 miles, respectively. For every exception type, the Predictive Coach phase had lower vehicle average weekly rates compared to the Baseline phase.

Table 4. Average vehicle weekly rate of all risky driving behaviors per 1,000 miles traveled in each study phase for bus drivers

Risky Driving Type	Rate of Risky Driving per 1,000 Miles (SD) in Baseline Phase	Rate of Risky Driving per 1,000 Miles (SD) in Awareness Phase	Rate of Risky Driving per 1,000 Miles (SD) in Predictive Coach Phase
Overall	19.31 (21.36)	16.58 (17.82)	13.83 (15.83)
Excessive Speeding	4.62 (9.75)	0.97 (2.57)	1.71 (3.24)
Hard Cornering	14.58 (18.38)	15.51 (17.39)	12.02 (14.57)
Hard Braking	0.12 (0.48)	0.11 (0.62)	0.10 (0.97)
Rapid Acceleration	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)

The following figures show the weekly rate of risky driving events calculated per bus plotted across all weeks in study. Figure 11 presents the rate of overall risky driving events per 1,000 driving miles, and Figure 12, Figure 13, Figure 14 present the rates of excessive speeding, hard cornering, and hard braking events per 1,000 driving miles, respectively. In Figure 11 the vehicle rates are generally clustered under 20 events per 1,000 miles. However, the rates have a downward trend over the study period. The specific event type plots illustrate hard cornering and excessive speeding event rates following a similar pattern, although the frequency of hard cornering events was higher than speed events. The rates of hard braking events per vehicle were rarely above 2 hard braking events per 1,000 miles.

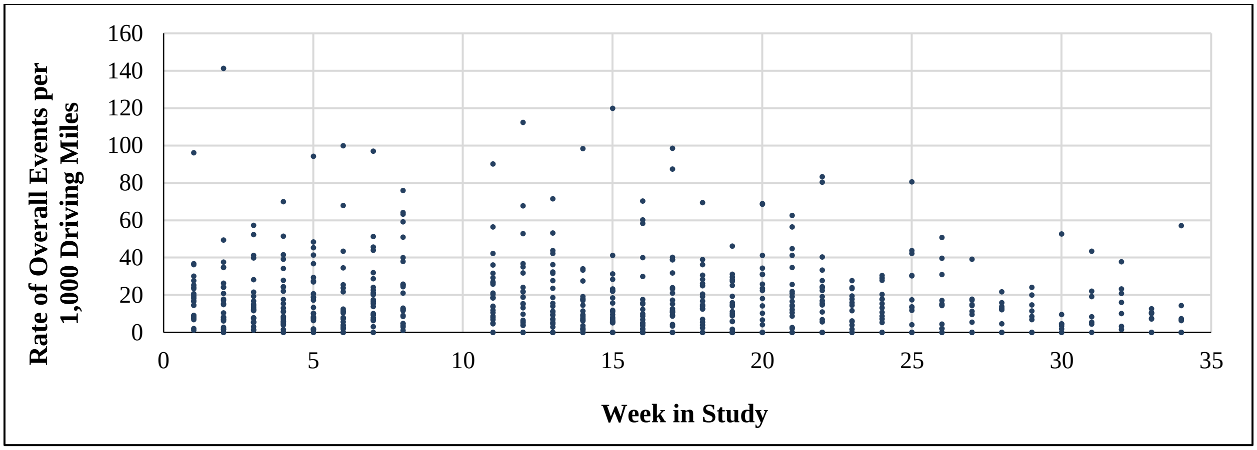

Figure 11. Weekly Rate of Overall Risky Driving Events per 1,000 Miles Across All Buses and Weeks.

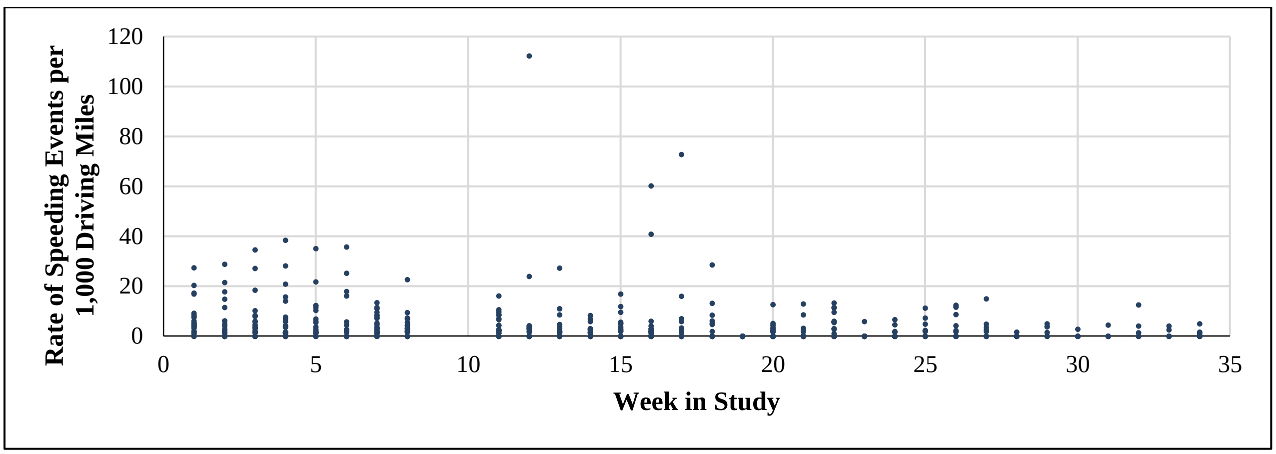

Figure 12. Weekly Rate of Excessive Speeding Events per 1,000 Miles Across all Buses and Weeks.

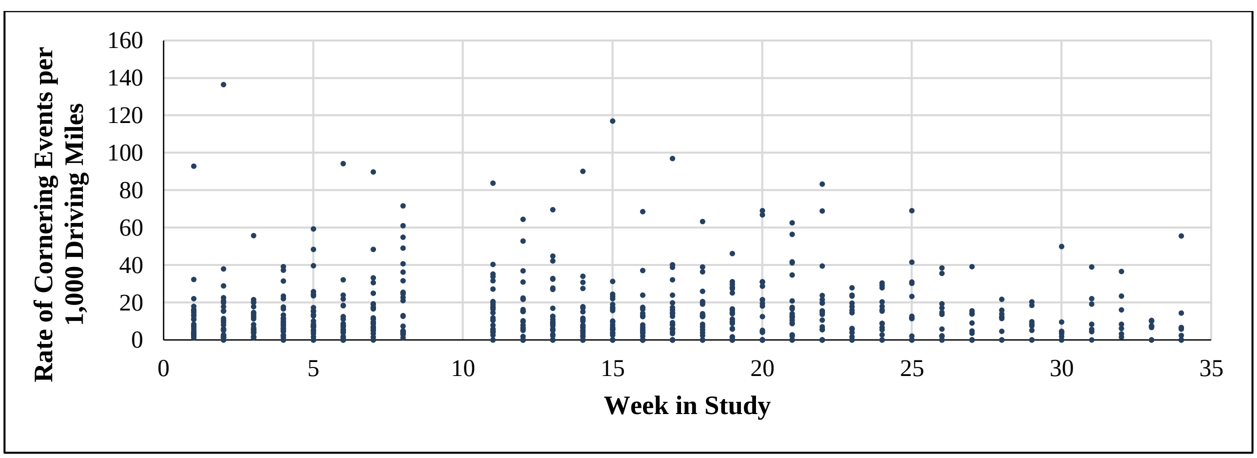

Figure 13. Weekly Rate of Hard Cornering Events per 1,000 Miles Across all Buses and Weeks.

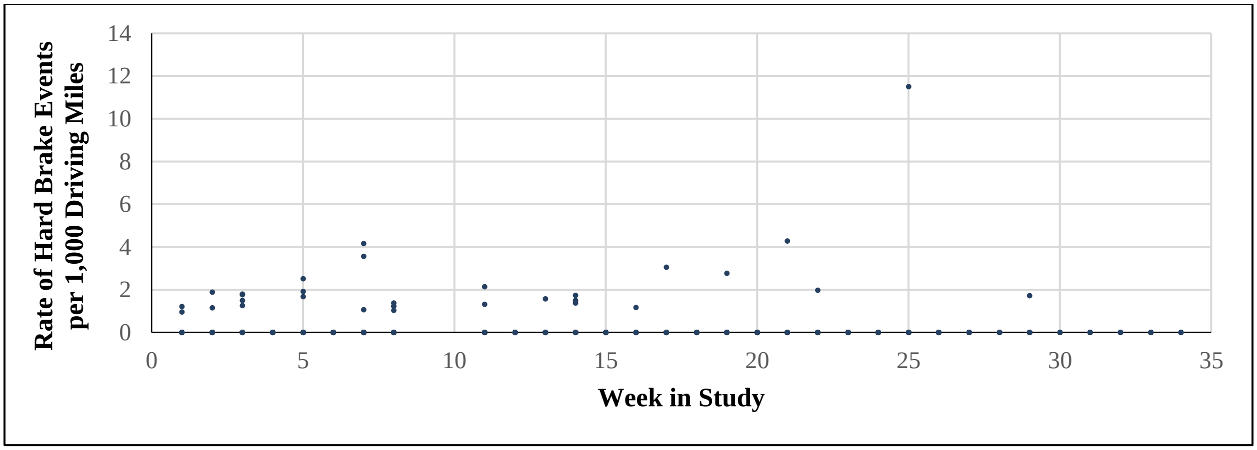

Figure 14. Weekly Rate of Hard Braking Events per 1,000 Miles Across all Buses and Weeks.

Overall Risky Driving Events

A Poisson mixed-effects regression model comparing the Baseline, Awareness, and Predictive Coach Training phases on the rates of all risky driving events per mile for bus drivers showed a significant difference between the Baseline phase and the Predictive Coach phase. The model estimates, with p-values, are included in Table 5 below. The Predictive Coach phase was found to be significantly different from Baseline ($p < 0.0001$). However, the Awareness phase was not statistically significantly different from the Baseline phase ($p = 0.4012$). The Predictive Coach phase (estimate = -0.3527) was associated with lower risky driving rates compared to the Baseline phase, indicated by its negative estimate value.

Table 5. Results from Poisson mixed-effect regression model, modeling the effect of study phase on rates of overall risky driving types for bus drivers

Parameter	**Phase**	**Estimate**	**Standard Error**	***df***	***t*-value**	***p*-value**
Intercept		-3.9451	0.0867	24	-45.51	<.0001
Week Phase	**Awareness**	-0.0416	0.0495	578	-0.84	0.4012
Week Phase	**Predive Coach**	-0.3527	0.0377	578	-9.37	<.0001*
Week Phase	**Baseline**	0.0000	0.0000	0	.	.

In Table 6, the Type III test of the fixed effects indicates the fixed effect factor of study phase contributes significantly to the model of risky driving event rate for bus operators.

Table 6. Type III test of fixed effects from Poisson mixed-effect regression model

Effect	**Numerator DF**	**Denominator DF**	***F* Value**	***p*-value**
Study Phase	2	578	43.88	<.0001*

** denotes statistically significant result at alpha = 0.05*

In Table 7, each phase is compared to each other phase in a pairwise analysis. The RR for each comparison, with adjusted CI and p-value, is listed in Table 7. The significance level for this analysis has been adjusted with a Turkey adjustment for bus drivers, the Awareness phase and Baseline phase did not show a significant difference in rate of overall risky driving events (Awareness vs Baseline RR = 0.9592, CI = [0.8703, 1.0572]). The Predictive Coach phase did show a significantly lower rate of overall risky driving events per mile when compared to the Baseline phase (Predictive Coach vs Baseline RR = 0.6940, CI = [0.6527, 0.7568]). In other words, assuming mileage was the same, a bus driver that performed 100 risky driving events in the Baseline phase, would be expected to the perform about 96 risky driving events during the Awareness phase and 69 risky driving events in the Predictive Coach Training phase. The Predictive Coach phase also had a significantly lower rate of overall risky driving events per vehicle mile traveled compared to the Awareness phase (RR = 0.7327, CI = [0.6525, 0.8227]).

Table 7. Risk ratio and confidence interval calculations comparing the rate of overall risky driving in each study phase for bus drivers

Comparison	RR Estimate	Adj CI	*df*	*t*-value	*p*-value
Predictive Coach vs. Awareness	0.7327*	(0.6525, 0.8227)	578	-5.27	<.0001
Awareness vs. Baseline	0.9592	(0.8703, 1.0572)	578	-0.84	0.4012
Predictive Coach vs. Baseline	0.6940*	(0.6527, 0.7568)	578	-9.37	<.0001
** denotes statistically significant result at alpha = 0.05*					

Specific Risky Driving Behaviors

The following section presents results of the bus driver analysis for specific risky driving behaviors. A separate Poisson mixed-effect regression model was built for each risky driving behavior. The model results for all risky driving behaviors are included in Table 8 below. The Awareness phase showed a significantly lower rate of excessive speeding events per mile compared to the Baseline phase (RR = 0.3126, CI = [0.2233, 0.4375]). The rate of excessive speeding events in the Awareness phase was approximately one third the rate of excessive speeding events in the Baseline phase. The Awareness phase had a significantly higher rate of hard cornering events than the Baseline phase (RR = 1.1556, CI = [1.0425, 1.2811]).

The Predictive Coach phase had a significantly lower rate of excessive speeding events per mile compared to the Baseline phase (RR = 0.3662, CI = [0.3002, 0.4469]). The rate of excessive speeding events in the Predictive Coach phase was just over a third of the rate observed in the Baseline phase. Hard cornering event rates were also significantly lower in the Predictive Coach phase compared to the Baseline phase (RR = 0.8104, CI = [0.7478, 0.8783]).

The Predictive Coach phase and Awareness phase had significantly different rates of hard cornering events (RR = 0.7013, CI = [0.6203, 0.7928]). The expected rate of hard cornering events per mile in the Predictive Coach phase was over two-thirds the rate in the Awareness phase.

Table 8. RR and CI comparing specific risky driving behavior rates in each study phase for bus drivers.

Risky Driving Type	Comparison	RR Estimate	Adj CI	*df*	*t*-value	*p*-value
Excessive Speeding	Predictive Coach vs. Awareness	1.1717	(0.7989, 1.7186)	578	0.81	0.4168
Excessive Speeding	Awareness vs. Baseline	0.3126*	(0.2233, 0.4375)	578	-6.79	<.0001
Excessive Speeding	Predictive Coach vs. Baseline	0.3662*	(0.3002, 0.4469)	578	-9.91	<.0001
Hard Cornering	Predictive Coach vs. Awareness	0.7013*	(0.6203, 0.7928)	578	-5.68	<.0001
Hard Cornering	Awareness vs. Baseline	1.1556*	(1.0425, 1.2811)	578	2.76	0.0060
Hard Cornering	Predictive Coach vs. Baseline	0.8104*	(0.7478, 0.8783)	578	-5.14	<.0001
Hard Braking	Predictive Coach vs. Awareness	0.4539	(0.0913, 2.2563)	578	-0.97	0.3337
Hard Braking	Awareness vs. Baseline	0.9311	(0.2824, 3.0704)	578	0.12	0.9065
Hard Braking	Predictive Coach vs. Baseline	0.4226	(0.1282, 1.3936)	578	-1.42	0.1568

** denotes statistically significant result at alpha = 0.05*

Light Vehicles

As mentioned above, drivers were not assigned Predictive Coach trainings based on their driving performance in light-vehicles. However, these data were collected to examine if improved safety performance transferred to light-vehicle driving. Similar to the analysis above, Figure 15 shows the vehicle average weekly rate of all risky driving behaviors per 1,000 miles traveled was calculated for each study phase.

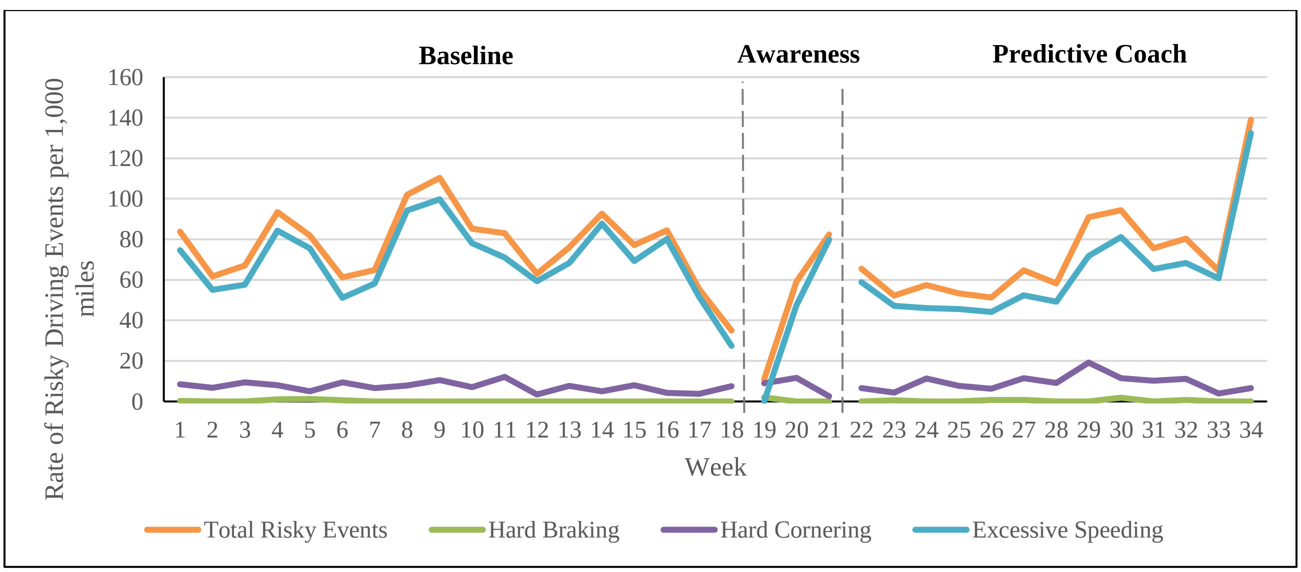

Figure 15. Average Rates of Light Vehicle Drivers' Risky Driving per 1,000 Miles Across All Drivers.

Table 9 shows the averages for each of the risky driving behaviors. The weekly rate of overall risky driving events per 1,000 miles was 73.69 in the Baseline phase, 74.66 in the Awareness phase, and 80.81 in the Predictive Coach phase.

Table 9. Average vehicle weekly rate of all exceptions per 1,000 miles traveled in each study phase for light vehicles

Risky Driving Type	Rate of Risky Driving per 1,000 Miles (SD) in Baseline Phase	Rate of Risky Driving per 1,000 Miles (SD) in Awareness Phase	Rate of Risky Driving per 1,000 Miles (SD) in Predictive Coach Phase
Overall	73.69 (26.70)	74.67 (32.18)	80.81 (53.59)
Excessive Speeding	66.39 (25.46)	66.69 (30.28)	66.07 (37.26)
Hard Cornering	7.08 (3.97)	7.98 (7.04)	14.23 (19.29)
Hard Braking	0.21 (0.59)	0.00 (0.00)	0.50 (1.20)
Rapid Acceleration	0.02 (0.14)	0.00 (0.00)	0.00 (0.00)

The figures below plot the event rates per 1,000 driving miles for each week of the study and light vehicle ID. Figure 16, Figure 17, and Figure 18 show the rates of overall events, hard cornering events, and excessive speeding events, respectively (plots are not shown for hard braking and rapid acceleration as they were infrequent). In Figure 16, all light vehicles show similar event rates early in the study, up to week 7. However, at week 10, the difference in event rates between vehicles grows; vehicle 1503 and vehicle 1504 show a similar trend in event rates across the study weeks, but vehicle 1501 event rates rise around week 20 through the end of the study. This pattern was observed in the hard cornering event plot in Figure 17 and excessive speeding event plot in Figure 18.

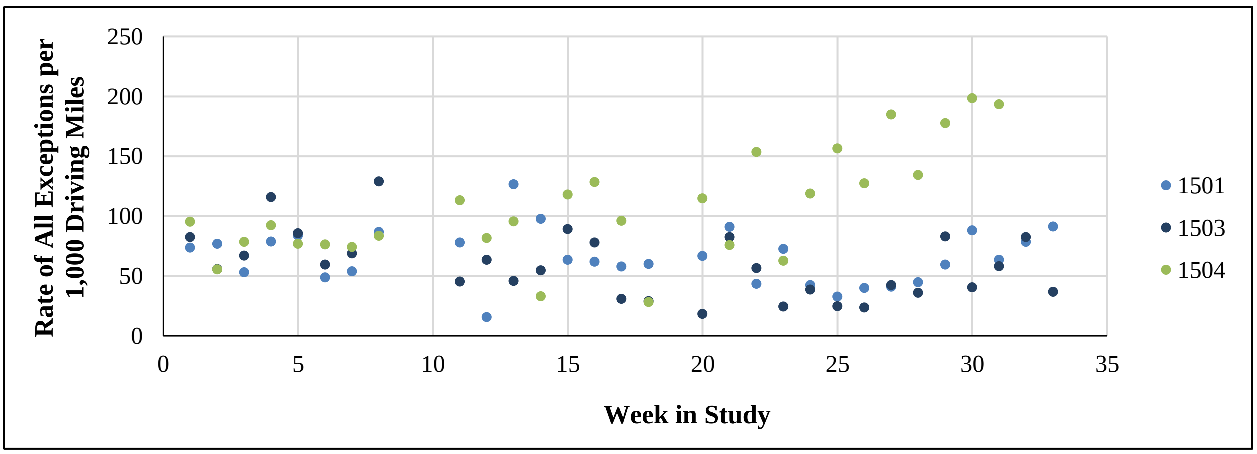

Figure 16. Weekly Rate of Overall Events per 1,000 Miles for Each Week in Study by Light Vehicle.

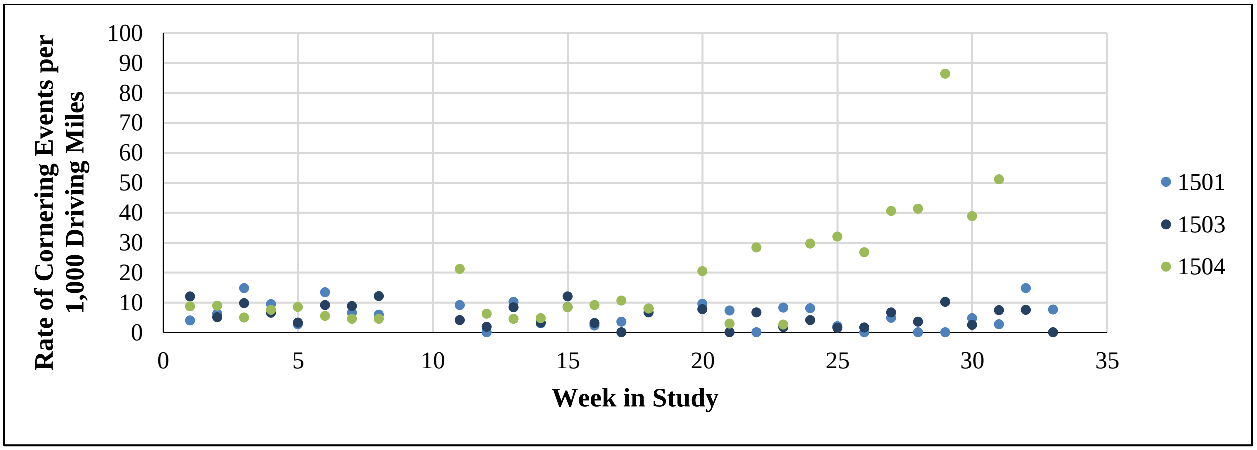

Figure 17. Weekly Rate of Hard Cornering Events per 1,000 Miles for Each Week in Study by Light Vehicle.

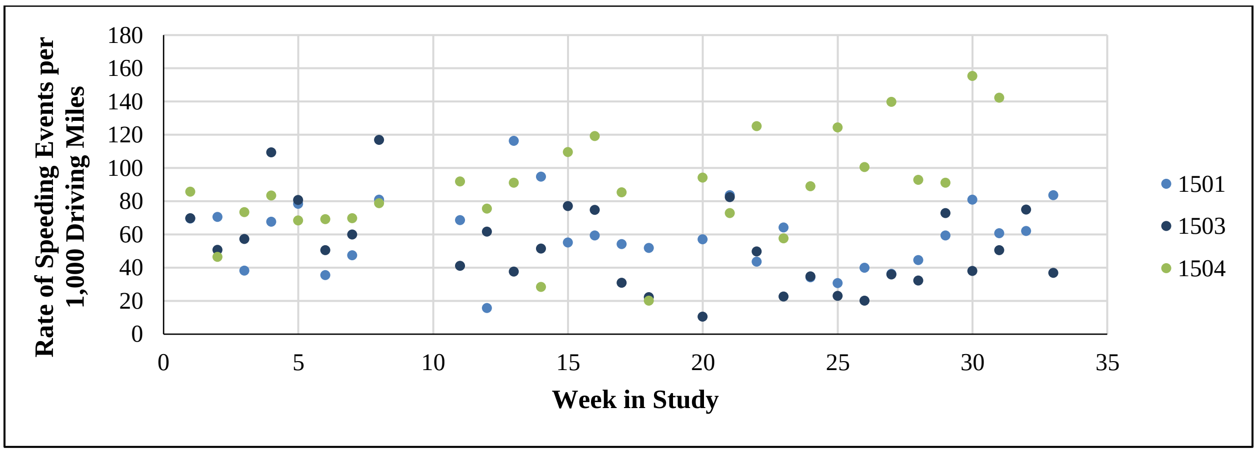

Figure 18. Weekly Rate of Excessive Speeding Events per 1,000 Miles for Each Week in Study by Light Vehicle.

Overall Risky Driving Events

Table 10 shows the results of the Poisson mixed-effect regression model comparing the light vehicle drivers' rate of overall risky driving events in each of the three study phases. Both the Awareness (estimate = -0.0188) and Predictive Coach (estimate = -0.0500) phases have parameter estimate values that are not statistically significant in the model ($p_{Awareness} = 0.8245$; $p_{PC} = 0.1995$).

Table 10. Results from Poisson mixed-effect regression model, modeling the effect of study phase on rates of all risky driving events for light vehicle drivers.

Parameter	Phase	Estimate	Standard Error	*df*	*t*-value	*p*-value
Intercept		-2.6019	0.1334	2	-19.51	0.0026
Study Phase	**Awareness**	-0.0188	0.0843	83	-0.22	0.8245
Study Phase	**Predictive Coach**	-0.0500	0.0387	83	-1.29	0.1995
Study Phase	**Baseline**	0.0000	0.0000		.	.

The Type III test of the fixed effect for study phase (in Table 11) confirms that study phase does not contribute significantly to the model of even rate for light vehicles.

Table 11. Type III test of fixed effects from the Poisson mixed-effect regression model for light vehicles

Effect	Numerator DF	Denominator DF	*F* Value	*p*-value
Study Phase	2	83	0.84	0.4369

RR estimates for phase comparisons are included in Table 12. As the model indicated above, the phases showed no significant differences from each other in rates of all events.

Table 12. RR and CI calculations comparing the rate of all risky driving events in each study phase for light vehicle drivers

Comparison	RR Estimate	Adj CI	*df*	*t*-value	*p*-value
Predictive Coach vs. Awareness	0.9693	(0.8156, 1.1519)	83	-0.36	0.7200
Awareness vs. Baseline	0.9814	(0.8299, 1.1606)	83	-0.22	0.8245
Predictive Coach vs. Baseline	0.9512	(0.8809, 1.0273)	83	-1.29	0.1995

Specific Behavior Types

An analysis of light vehicle driver data compared rates of specific risky driving behaviors in all study phases. For each risky driving behavior, a Poisson mixed-effect regression model was built to measure how study phase impacted the rate of that risky driving behavior. Results from the individual models for excessive speeding and hard cornering are shown in Table 13. Due to very low counts of hard braking and rapid acceleration events in the light vehicle data, no modeling was performed to assess differences by study phase.

Excessive speeding event rates were found to be significantly lower for the Predictive Coach phase compared to the Baseline phase [RR = 0.8873, CI = (0.8172, 0.9634)]. The hard cornering event rate was significantly higher for the Predictive Coach phase compared to the Baseline phase (RR = 1.5776, CI = [1.2625, 1.9712]), but no significant differences were observed between the Predictive Coach and Awareness phases and the Awareness and Baseline phases.

Table 13. RR and CI comparing specific risky driving event type rates in each study phase for light vehicles

Risky Driving Type	Comparison	RR Estimate	Adj CI	*df*	*t*-value	*p*-value
Excessive Speeding	**Predictive Coach vs. Awareness**	0.9006	(0.7509, 1.0802)	83	-1.15	0.2553
Excessive Speeding	**Awareness vs. Baseline**	0.9852	(0.8261, 1.1749)	83	-0.17	0.8669
Excessive Speeding	**Predictive Coach vs. Baseline**	0.8873*	(0.8172, 0.9634)	83	-2.89	0.0049
Hard Cornering	**Predictive Coach vs. Awareness**	1.6246	(0.9312, 2.8343)	83	1.73	0.0866
Hard Cornering	**Awareness vs. Baseline**	0.9710	(0.5593, 1.6859)	83	-0.11	0.9158
Hard Cornering	**Predictive Coach vs. Baseline**	1.5776*	(1.2625, 1.9712)	83	4.07	0.0001

** denotes statistically significant result at alpha =0.05*

User Opinions of Predictive Coach

Due to COVID-19 travel restrictions, the research team was unable to collect supervisor and driver opinions in-person. However, the research team was able to collect qualitative data from two supervisors and two drivers that participated in the program.

The supervisors indicated the drivers, overall, did not like the Predictive Coach program. Some drivers complained to the supervisors the trainings were too long and that bumpy roads triggered alerts for hard cornering. Some drivers also complained to supervisors the real-time alerts in the cab were annoying. However, it seemed as if most of these complaints were associated with the Geotab device and not the actual Predictive Coach program. Despite these complaints, the supervisors indicated the Predictive Coach training likely made their drivers drive safer, but they were unclear if the program was useful in reducing drivers' risky driving habits. Overall, the supervisors strongly agreed the Predictive Coach training program was a good safety intervention and easy to use. Although supervisors believed the program was useful and resulted in safer drivers, they would not recommend the program to other transit agencies. However, the supervisors generally liked the innovated training component and said they would recommend Predictive Coach to other transit fleets with two minor adjustments. First, remove the real-time alert. As mentioned above, the drivers were annoyed and confused by the alerts and often did not understand why the alerts were generated. However, the research team suspects much of this confusion came from drivers that replaced furloughed or laid off drivers due to COVID-19, and thus, joined the fleet after the initial driver training. In the future, RMJ Technologies can address this concern with more in-depth driver training and ensuring Predictive Coach awareness training is included in new hire orientation. Second, the supervisors indicated that some drivers were assigned the same training sessions multiple times, which was confusing and decreased the trainings' impact. In the future, developing additional training or adjusting the algorithms to limit the number of times drivers were assigned the same trainings.

The drivers offered very positive opinions of the Predictive Coach training. Drivers indicated the Predictive Coach program was helpful in improving their safe driving habits and reducing their risky driving habits. Additionally, they believed the Predictive Coach program was a good safety intervention. One of the drivers indicated they would recommend Predictive Coach to other transit fleets; however, the other driver was hesitant in recommending the program. When asked why, the driver indicated the process of accessing and completing the training was difficult, the training could have been more engaging, and the training content could have been more relevant to transit operations. However, the driver would recommend Predictive Coach if the following concerns were resolved. First, it was unclear exactly why trainings were assigned to the drivers. This could be addressed with more thorough training or additional information provided during the training assignment. Second, drivers were confused on how to access and complete the trainings. As mentioned above, Predictive Coach assigned trainings via email; however, drivers at this fleet never had email accounts and were unfamiliar with the process. In the future, this issue could be addressed by developing additional methods of assigning trainings and communicating with drivers (i.e., through an electronic dispatching device). Finally, the driver suggested the trainings should be more specific to the transit industry. This issue could be addressed by developing a separate training series dedicated to the transit industry.

Plans for Implementation

The initial development of Predictive Coach was based on proactive defensive driving. Predictive Coach was designed primarily for light duty service fleets; however, defensive driving relates to all drivers, regardless of profession or the type of vehicle driven. As the transit industry was not the immediate target market for Predictive Coach, RMJ Technologies was unsure how effective the innovative training concept would be for bus drivers. However, the results from this project confirmed that proactive defensive driving training and the innovative training delivery concept was relevant and effective for occupational drivers in the transit industry. The results showed that the basic foundational safe driving behaviors deteriorate overtime, and bus drivers do benefit from targeted training and increased accountability for their driving habits. As these results show, there is a need and benefit to transit fleets. Thus, RMJ Technologies plans to expand their target market to include the transit industry. Further, RMJ Technologies is explore the possibility to develop more specialized and thorough transit-specific training. This would help the Predictive Coach platform gain additional traction in the transit industry in hopes of reducing fleet risk and improving safe driving.

The innovative training concept offered by Predictive Coach was built to be open to the various types of hardware and software used by transportation fleets. Currently, Predictive Coach works with Geotab, an inexpensive, popular, and powerful open-source OSM service provider. However, Predictive Coach can be easily integrated for use in any user interface from an OSM system provider. Based on the results of this project, RMJ Technology will accelerate their efforts to incorporate the training offered through Predictive Coach into other telematics systems. For example, Predictive Coach is close to finalizing its own application programming interface to permit any organization to integrate Predictive Coach into their existing platform. The significant safety improvement results from this study will help Predictive Coach expand their market share within the telematics industry. Furthermore, Predictive Coach will focus on developing their own basic user interface and software gateway in 2021. Currently, end users access Predictive Coach through the Geotab user interface. By developing a customized Predictive Coach user interface, an end user of any telematics provider will be able to connect with Predictive Coach and directly access to the Predictive Coach user interface.

In addition, to an expanding to the initially untargeted transit industry, this study also allowed the research team to investigate the use of Predictive Coach in combination with other in-cab monitoring technologies, specifically an in-cab video telematic solution. In this study, Keolis happened to already be using a leading camera solution provider, Lytx®'s DriveCam®, and was recognized by that camera provider as a strong and successful user. Previous research by this research team found in-cab video monitoring technologies offer significant safety benefits (*5*). In light of the significant safety improvements of Predictive Coach beyond the already improve safety performance from DriveCam®, Predictive Coach identified an entirely new market possibility. Predictive Coach is now planning on integrating with an in-cab video telematics provider. Results from this study made this a possibility.

Conclusions

This study offered RMJ Technologies an opportunity to investigate how their innovative training program and delivery method, Predictive Coach, would function in a transit setting. Results from this study were clear: the Predictive Coach program is a valuable asset to a fleet interested in improving safety. It offers fleets an easy approach to track risky driving behaviors by partnering with Geotab (or other telematics providers in the future), provides an objective method of identifying drivers in need of training, offers targeted training courses based on individual driving habits, and automatically performs all these functions without fleet intervention. This process has the potential to help fleets demonstrate compliance to safety policies and reduce the burden on supervisors.

Results from this study showed the Predictive Coach program was associated with a reduction in bus drivers' risky driving behaviors. With the Predictive Coach program activated, the rate of overall risky driving in buses was significantly lower than the rate before the Predictive Coach program began. Results showed the rate of overall risky driving per 1,000 miles in buses was 31% lower during the Predictive Coach program compared to before the program began. When examining the specific risky driving behaviors, excessive speeding and hard cornering were most impacted by the Predictive Coach program. The rate of excessive speeding per 1,000 miles was 69% lower after drivers were introduced to the Predictive Coach program (but the training was not activated) and 63% lower during the Predictive Coach program compared to the Baseline phase. This small difference between the Awareness phase and Predictive Coach phase was not statistically significant. This means the Predictive Coach program maintained the reduced rate of excessive speeding after drivers were trained on how the program worked. Additionally, the rate of hard cornering per 1,000 miles in buses was 19% lower with the Predictive Coach program compared to Baseline and 54% lower compared to when drivers were introduced to the program but before the trainings were activated.

The results for the light vehicles did show an 11% reduction in excessive speeding events during the Predictive Coach program compared to the Baseline phase, but findings of overall safety improvement with the Predictive Coach program was limited. However, this was expected. As specific drivers were not tracked when operating the light vehicles, they were not assigned training based on their performance. In fact, the rate of hard cornering per 1,000 miles in light vehicle was higher in the Predictive Coach phase compared to the Baseline phase. This finding illustrates one of the reasons Predictive Coach is important beyond traditional telematics. Drivers knew the devices were installed in the light-vehicles (i.e., they still received the in-cab alerts anytime a risky driving behavior was detected); however, they knew they were not being held accountable for the behavior. The Predictive Coach system adds that extra layer of accountability for performing risky driving behaviors. It also provides a consequence for performing multiple risky drivers. This result supports previous research showing lasting behavior change is unlikely without a consequence (*16*).

Although there has been transit-specific research examining the innovative training concept offered by Predictive Coach, the results in this study do support previous research examining the effectiveness of driver coaching using data from OSM devices. Previous research shows that provided individualized driver coaching based on OSM data results in significant safety improvements (*5,9,17*). Additionally, Predictive Coach conducted a separate pilot test with only light-vehicle drivers, with statistically significant reductions in risky driving (*18*). The light vehicle drivers that were exposed to the Predictive Coach program significantly reduced their excessive speeding, hard braking, and hard cornering by 73.9%, 52.2%, and 51.4%, respectively. However, it was unclear if the results from light vehicle drivers would generalize to a transit fleet, as transit drivers are more highly trained and under stricter regulations.

As described above, the participating Keolis fleet was already safe. They had a long history of participating in a leading video-based telematics program, and the onsite supervisor had been recognized for excellent driver coaching. With this in mind, any positive results from the Predictive Coach program would have been impressive. However, a statistically significant reduction of 63% in excessive speeding events demonstrates the value of Predictive Coach. Even safe fleets can become safer with the Predictive Coach program.

Limitations

Although this study found positive results and used a strong methodology and analysis approach, there were several limitations and obstacles. The largest limitation of this study was due to the global pandemic associated with COVID-19. As mentioned above, COVID-19 caused major disruptions in the participating transit fleet. The fleet was forced to reduce its level of service by a minimum of 40% halfway through the Baseline phase. As a result, the fleet was forced to furlough and/or layoff drivers, some of which were participating in this study. This significantly reduced the number of drivers that had complete data sets in all phases of the study. This impacted which analysis the research team was able to use.

A within-driver comparison is the ideal analysis scenario for a study investigating the impact of a treatment on an outcome. However, this study was affected by participant dropouts, leaving few participants with complete data in each study phase. In addition, the driver ID was missing from approximately 10% of bus driver events and all light vehicle driver events. As a result of these limitations, the current study did not control for driver in the assessment of study phase impact on safety event behavior. The analysis did control for vehicle ID as a surrogate for individual drivers, as certain vehicle IDs did show distinct behavior patterns. Participant dropout is a potential issue in any study, especially those involving the driving industry (as employee attrition is common). In this study, Covid-19 exacerbated employee attrition and limited the options typically available to communicate with and monitor the participating fleet and participants. The research team often is able to include a boots-on-the-ground approach to visit the data collection site, maintain data collection devices, and promptly correct issues; however, Covid-19 restricted the research team from physically traveling to the research site.

In addition to losing some drivers due to terminations and furloughs, both onsite project champions left the fleet during the study. These individuals were instrumental in setting up the project, identifying drivers and vehicles to participate in the study, delivering communication about the project to drivers, and keeping the research team up to date on scheduled bus routes and levels of service. Although their replacements were incredibly helpful in the successful completion of the project, it appeared the new onsite supervisors did not know the project's backstory, which vehicles were participating in the study, and did not become fully invested in the user testing. Thus, several of the buses with Geotab devices had been placed out of service soon after the Predictive Coach phase began. This resulted in losing risky driving event data.

COVID-19 also impacted the research team's ability to collect supervisor and driver opinion data. The original plan included the principal investigator traveling to the data collection site to collect driver opinion data in person. This was not possible with local and company policy. The research team pivoted to collect these data via telephone. However, this limited the number of drivers that participated, and researchers were only able to contact two drivers that participated in the program.

As mentioned above, hard braking events were infrequently observed in the data set. With infrequent behaviors, the strength of the analysis in identifying significant differences improves with increases in the amount of data. In future assessments, a larger sample of drivers is likely needed to assess this behavior.

Conclusions and Lessons Learned

This study demonstrated an innovative training delivery concept developed by Predictive Coach was effective in reducing risky driving in transit operations. Risky driving was significantly reduced when the training program was activated, and specific instances of excessive speeding and hard cornering were significantly reduced. These safety improvements were beyond the safety improvements already achieved with video telematics. Although this study identified significant reductions in risky driving behaviors, we need follow-up testing with a larger sample of transit drivers to validate the results and to promote the adoption within the transit industry.

Results from this study will provide RMJ Technologies valuable information to help Predictive Coach succeed. First, this showed the importance of carefully examining the data produced by the telematics device and in-person follow-ups. As COVID-19 limited in-person visits, RMJ Technologies can develop new strategies to ensure data quality. Second, the driver opinion data highlight the importance of continued driver awareness to ensure all new drivers receive the same training on Predictive Coach. It appeared drivers who joined Keolis after the study began did not fully understand how the telematics device operated and how trainings were assigned. Third, although risky driving reduced during the Predictive Coach intervention and one driver indicated the training content was relevant, there is room for improvement. RMJ Technologies can consider develop transit-specific training content to make it more relevant to the transit industry. Additionally, now that RMJ Technologies knows the Predictive Coach program is effective in reducing bus drivers' risky driving, additional training modules can be developed to limit redundancies. RMJ Technologies can engage the transit industry to identify additional opportunities and needs for additional automatic, individiualized, online services. Finally, RMJ Technologies learned there may be a need to offer the training content in additional languages.

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