Automated Enforcement and Detection of Driver Risk

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Executive Summary

Can we use automated enforcement data to improve road safety?

Municipalities and law enforcement agencies across Alberta are sitting on a rich store of traffic safety information. Every day, cameras in our communities record the licence plates of drivers who exceed posted speed limits, run red lights and speed through intersections and school zones. These cameras, called automated photo enforcement technologies, include Intersection Safety Devices and Photo Radar Cameras. The information they collect is stored and used to ticket the registered owners of the vehicles involved in these dangerous behaviours.

Could this data be put to work in other ways? Could this information be used to identify those drivers who repeatedly break traffic safety laws and put all of us at risk? That's the question the Capital Region Safety Partnership (CRISP) asked in 2010. The same year, an Australian study showed that automated enforcement (AE) data could be used as an indicator of driver behaviour – but more study was needed to understand how this data could be applied to improve road safety.

In 2012, CRISP partners supported a proof-of-concept study by a researcher from the University of Alberta Criminology program to explore the untapped potential of automated enforcement data.

The Study

The purpose of this study was to determine how data collected through automated enforcement technologies could be used to improve road safety in the Capital Region.

Four types of data were used:

- *Automated enforcement data* from the City of Edmonton and Strathcona County for 2010-2011 – a total of 669,186 violations associated with 378,138 vehicles.
- *Collision data* from the City of Edmonton and Strathcona County for 2010-2011, including the total number of collisions and total injury collisions associated with each given vehicle.
- *Driver records*[*] of the registered owners of all vehicles in the study, showing all driving-related charges, most of which have a numerical demerit rating.
- *Criminal records** of the registered owners of all vehicles in the study, including all listed charges and convictions.

The AE data was used to create 12 groups of drivers, based on the number of AE violations associated with a single vehicle – from 1 violation to 12 or more. The researcher then looked for relationships between the number of AE violations and collision involvement, other traffic violations and criminal history.

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[*] Driver records and criminal records were stripped of all personal information before being provided to the researcher. Individuals were identified solely by an associated license plate to protect anonymity.

Key Findings

- **Is there a relationship between AE violations and collision involvement?**

The study found a strong, positive relationship between the number of AE violations and collision involvement. On average, drivers with more AE violations had more collisions than other drivers. Moreover, those drivers with 12 or more AE violations were involved in the highest proportion of *injury* collisions: 21% compared to 12-17% among drivers with fewer AE violations.

- **Is there a relationship between AE violations and other traffic violations?**

On average, those drivers with higher numbers of AE violations committed higher numbers of demerit-earning violations than did other drivers. For example, in this study the registered owners of vehicles with the most AE violations received, on average, three demerits per year of driving, compared to a random population average of less than one demerit per year of driving.

- **Is there a relationship between traffic violations and criminal history?**

Drivers with criminal records were more likely than drivers without criminal records to have higher numbers of AE violations. These drivers were also more likely to commit demerit-earning violations than drivers with the same number of AE violations who do not have criminal records.

- **What proportion of drivers commit AE violations across jurisdictions?**

Of the 378,138 vehicles with at least one AE violation, 20,915 or 5.3% committed AE violations in both the City of Edmonton and Strathcona County. Roughly 10% of drivers with only 2 AE infractions had committed violations in both jurisdictions. In comparison, over 30% of the most prolific offenders had violations in both the City of Edmonton and Strathcona County. Generally speaking, drivers with more AE violations were more likely to offend in both jurisdictions.

Conclusions

This study found positive relationships between AE violations and other traffic-related behaviours. The study also found that drivers with high numbers of AE violations were more likely than other drivers to be involved in criminal activities.

Unfortunately, the data do not allow us to say that AE violations caused (or were caused by) collisions, criminal activity, or other traffic violations. Despite this, the findings certainly indicate that AE data can add to our general understanding of driver behaviour, and can be used to identify at least some of the high-risk driving population.

Further research is needed to refine our methods of identifying high risk drivers. There is no doubt that AE data can play an important role in the development of more effective intervention strategies that will make our roadways and communities safer for everyone.

I. Introduction

History of Project Mercury

Automated photo enforcement technologies are a relatively new traffic safety tool, several forms of which are now deployed throughout Edmonton, Strathcona County and St. Albert. In the Edmonton region, two different types are used: Intersection Safety Devices (ISDs), and Photo Radar Cameras (PRCs). The use of these automated safety tools has resulted in large numbers of license plates with associated lists of infractions being stored in police databases. Currently, the sole use of this data is to provide proof of the infractions for the legal proceedings associated with the violations.

Preliminary studies conducted in 2010 in Australia indicate the viability of using data stored by automated enforcement devices as one indicator of driver behavior (Paterson, 2010). However, the overall uses of this data are still relatively unexplored. Recognizing this untapped potential, Gerry Shimko, the Executive Director of Edmonton's Office of Traffic Safety (OTS) and RCMP Sergeant Chris Narbonne outlined a possible OTS inquiry on the matter in November 2010. The general objective of such an exploration would be to determine the extent to which data collected by automated enforcement technologies could be used to improve road safety in the Capital Region Intersection Safety Partnership (CRISP) area.

January to April of 2012 saw a proof-of-concept project conducted by this researcher as part of a University of Alberta Criminology placement program. The proof-of-concept used automated enforcement data from the Sherwood Park area, and indicated the validity of further investigation. The current project has been made possible through funding in the form of the Roger S. Smith Undergraduate Student Research award, as well as the support of the Edmonton Office of Traffic Safety. This study is the first large-scale investigation into the uses of automated enforcement data from the Edmonton region, and represents a first step into a promising field of inquiry.

Study Objectives

This study aims to provide insight into the possible uses of automated enforcement(AE) data.
In order to do so, it has focused on the following questions:

1. Is there any relationship between automated enforcement violation rates and collision involvement?
2. Is there any relationship between drivers' levels of automated enforcement violations and other traffic violations?
3. Is there any relationship between drivers' levels of automated enforcement violations and criminal history?
4. What is the extent of cross-jurisdictional traffic violations, and what population segment is committing these violations?

5. Does automated enforcement data show promise to identify high - risk drivers or otherwise make a meaningful contribution to traffic safety and intelligence?

To begin, terms will be defined and related literature will be addressed. Next, the data and methodology will be described. This will be followed by the study findings, as well as analysis and discussion thereof. The possible directions for future research and overall conclusions will be addressed last.

Definitions

Collision Event: The series of occurrences- typically in a short period of time- which encompass one or several motor vehicles being manoeuvred or acted upon in such a way that significant damage was caused to the vehicle(s), the passengers of the vehicle(s), or other private or public property including other vehicles and buildings. For example, a single vehicle colliding with a tree would count as a collision event, just as a four car pile-up would count as one collision event.

Collision Involvement/ Collision Involved Vehicle: For the purposes of this study, "collision involvement" refers to a single vehicle being involved in a collision event. Using this definition, a head-on collision between two vehicles would count as a single collision event but would have two collision-involved vehicles. In turn, a four-car pileup would qualify as a single collision event, but would have four collision-involved vehicles. This definition does not take into account which drivers were at fault. This study focuses much more heavily on collision involvement than it does collision events.

Intersection Safety Device (ISD): ISDs include cameras located in intersections that take a photograph of a vehicle's license plate should the vehicle a) pass through the intersection while driving at a speed exceeding the posted speed limit, b) pass through the intersection when the light has already turned red, or c) commit both violations simultaneously.

Photo Radar Cameras (PRC): PRCs are mobile cameras located at mid-block sections. They take a photograph of the license plates of vehicles which are exceeding the posted speed limit.

Automated Enforcement (AE): For the purposes of this study, Automated Enforcement (AE) is a general term referring to both PRCs and ISDs.

Risk: The likelihood of collision involvement by a given vehicle.

High-Risk Driver: Repeat offenders with patterned illegal driving behaviors (e.g.: recurring incidences of alcohol/drug impaired driving, traffic violations, collision involvement or suspended/ prohibited drivers) (Safety strategy 2015).

Related Literature

Broughton (2003) conducted a study in the UK which led to several relevant findings. First, drivers with a history of non-traffic offences were more likely to commit traffic offences than the general population. For example, men who committed between four and eight non-traffic offences also committed 6.5 times as many general traffic offences, and 18 times the number of serious traffic offences. The study also found that drivers who committed specific types of non-traffic crimes were more likely to fall within certain numerical ranges for traffic violations. As well, Broughton found that a quarter of all traffic offences between 1995 and 1999 were committed by the population segment which had also committed non-traffic offences in the same time period. Broughton conducted similar studies in 2006 and 2007, and returned similar findings in each case.

Junger et al. (2001) found that road users involved in crashes in the Netherlands had a disproportionately high rate of criminal history, with 31% of men involved in crashes having a criminal record, compared to the local average of 15% of men having criminal records. As well, risky driving behaviour was found to have a positive relationship with traffic crime, with risky behaviour defined as behaviours on the road which were likely responsible for collision involvement. The study found support for their hypothesis that a general tendency for risk taking and low self control are underlying factors which can lead to both criminal behaviour and risky behaviour in traffic. This last finding is similar to a conclusion drawn by Palk (2005) that drivers with lower self control are more likely to offend. One possible example of a population which has a general tendency for risk taking would be those who drive even while disqualified as reported in Rose (2000). Rose reports that drivers who operated a vehicle while disqualified were likely to be re-convicted within a year.

Chandraratna et al. (2006) found that the more traffic violations and speeding offences a driver has, the higher the likelihood of culpable collision involvement. Results also showed that committing general traffic violations increased the likelihood of culpable collision involvement slightly more than speeding. Each general violation increased likelihood of collision involvement by 7%, and each speeding violation 5%.

Cooper (1997) found that crash involvement was higher for drivers with greater numbers of speeding and non-speeding convictions, though the correlation was much higher for drivers with convictions for excessive speeding. Excessive speeding was defined as travelling more than 40 km/h over the limit. Excessive speeders were much more likely to be involved in speed related crashes, as well as crashes of greater severity than any other group.

Brace et al. (2009) provided a review of several existing research papers. The general findings were consistent with the other papers listed in this study. Overall, there was high degree of consensus with multiple studies demonstrating a positive relationship between criminal behavior and involvement in traffic offences. There was also strong support for work showing connections between general involvement in antisocial behaviours and risky driving behaviour, as well as between criminal history and crash involvement.

II. Data

Intersection Safety Device/ Photo Radar

Intersection safety device and photo radar data for 2010 and 2011 was provided by ACS. ACS is the company currently responsible for storage of all data collected by automated enforcement for both the City of Edmonton as well as Strathcona County. The data stored by ACS includes the date, time, location, speed and license plate number of an offending vehicle, as well as an associated photograph of the incident. Each violation is recorded as a separate entry in the system, and goes through a series of checks to ensure that there are no factors in place which could prevent a ticket from being lawfully issued to the registered owner of the vehicle. ACS provided the entire set of violation records for the City of Edmonton and Strathcona County in 2010-2011, which numbered in at 669,186 violations associated with 378,138 vehicles.

Collision Data

Collision Data for 2010/2011 was retrieved from three separate sources. The first was the Royal Canadian Mounted Police PROS (Police Reporting of Occurrence System), our source of collision data for Strathcona County. The data supplied to us was for public property collisions only, and included a list of license plates with associated collisions divided into the categories of either injury or property damage collisions. The second data source was the Edmonton Police Service (EPROS) database, which provided both public and private property collisions which occurred in the City of Edmonton. The data provided license plate and associated collision file numbers, and classified collisions as injury, property damage, or fatal. The date of the incident was also included. In order to be able to distinguish public and private property collisions in Edmonton, a third data source was required: the Edmonton Office of Traffic Safety Motor Vehicle Collision Information System (MVCIS). While MVCIS does not store any license plate information, it does contain file numbers for all public property collisions that occur in the City of Edmonton. By cross checking the file numbers from MVCIS with the EPS data, it was possible to filter out the private property collisions. The end result was that this study had access to all reported public property collisions which occurred in Edmonton and Strathcona County in 2010-2011. The total number of collision-involved vehicles on public property was 96,688. Vehicles with at least one associated AE violation accounted for 39,609 of these collision involvements.

Driver Records

Driver records provide a historical account of the driving-related charges that a driver has been convicted of over time. The majority of entries which appear on a driver record have an associated numerical demerit rating. Not every conviction has a number of demerits associated with it, however. For example, certain provincial violations do not add any demerits, though they are still entered on the driver record. ISD and PR violations do not appear on a driver record, nor do they have any associated number of demerits.

Driver records were retrieved from the PROS by Sgt. Narbonne. There were a number of cautionary steps that were undertaken to ensure that there was no breach of personal information. The full list of traffic history was obtained for each driver. Offences are not limited to 2010-2011 nor limited to the geographical areas of Edmonton and Strathcona County.

Criminal Records

The criminal records provide all listed charges and convictions that an individual has accrued over time. Each charge is associated with a date on which the charge was laid, as well as the relevant section of the Criminal Code to which the charge refers. Charges which result in conviction include a summary of the sentence given. Much like driver's records, this data was not limited to the years of data collection (2010-2011) or to charges and convictions which occurred in Strathcona County.

The records provided for this project had been stripped of any personal information such as birth date, name and so on. Each criminal record was identified solely by the associated license plate, with no other identifying information available to this researcher. At least one conviction was necessary for the purposes of this study for a driver to be recorded as having a criminal record.

III. Methodology

Random, High, and Top lists

Random (n=230)
License plates were randomly selected from the entire population of license plates associated with at least one automated enforcement violation in the 2010/2011 period (n=378,138). This sample size provides the findings for demerit ratings with a confidence level of 95% with a margin of error of 0.14. The "Random" group is intended to represent the average driver who has any automated enforcement violations.

High (n=98)
Plates were randomly selected from the population segment of license plates associated with 12 or more automated enforcement violations in the 2010-2011 period (n=1,117). This sample size provides the findings for demerit ratings with a confidence level of 95% with a margin of error of 0.37. This group is intended to represent drivers with clearly concerning driving habits as identified by automated enforcement methods.

Top (n=40)
The 40 plates associated with the highest number of automated enforcement violations in 2010/2011 were selected and designated as the “Top” offender group. The number of automated enforcement violations within this group ranged from 12 to 40. This group was included to see if there were any consistent trends within the most active offender population.

Because the above groups had areas of overlap, steps were taken to ensure that no plates appeared more than once in any of the lists.

Descriptive Statistics

The results of this study are of an exploratory nature, with the goal of identifying some of the implied relationships in the data. Caution is required when understanding these relationships as they are not necessarily causal. More details are discussed in the following section.

IV. Findings, Analysis, Discussion

Notes on Figure and Table Setup

For the sake of clarity, the label “number of AE violations” on the x axis describes 12 different groups of drivers. Each group is based on the number of AE violations committed in the 2010-2011 period by each of the vehicles in the group. This means that group “1” refers to all license plates associated with only 1 automated enforcement violation, a population of 240,474. Group 2 refers to all license plates associated with 2 automated enforcement violations in the same time period, a population of 73,287. Group 3 is composed of all those with three violations. There is a group for each number of AE violations up to the final group “12+” which consists of all license plates with twelve or more automated enforcement violations in 2010 and 2011, numbering 1,117.

1) Automated Enforcement Infractions vs. Collision Involvement

Figure 1 and Table 1 provide context for the following visualizations. Figure 1 is a visual representation of the relative sizes of the various offender groups. Table 1 provides numeric values and specific percentages which provide the foundation for several of the following tables.

Table 1

# of Infractions	# Vehicles/ Group	# Discrete Vehicles Involved in at Least 1 Collision	# Collision Involvements	% Vehicles Involved in at Least 1 Collision	Average Collisions/ Collision-Involved Vehicle	% Injury Collisions
1	240,474	17,549	19,584	7.3%	1.12	13.7%
2	73,287	7,808	8,789	10.7%	1.13	13.4%
3	30,467	3,951	4,526	13.0%	1.15	13.5%
4	14,479	2,160	2,522	14.9%	1.17	13.8%
5	7,697	1,238	1,452	16.1%	1.17	12.1%
6	4,352	769	908	17.7%	1.18	11.9%
7	2,550	497	598	19.5%	1.20	14.2%
8	1,597	294	352	18.4%	1.20	14.5%
9	1,014	224	279	22.1%	1.25	16.8%
10	643	139	164	21.6%	1.18	13.4%
11	461	81	99	17.6%	1.22	17.2%
12+	1,117	282	336	25.2%	1.19	21.4%

Figure 1

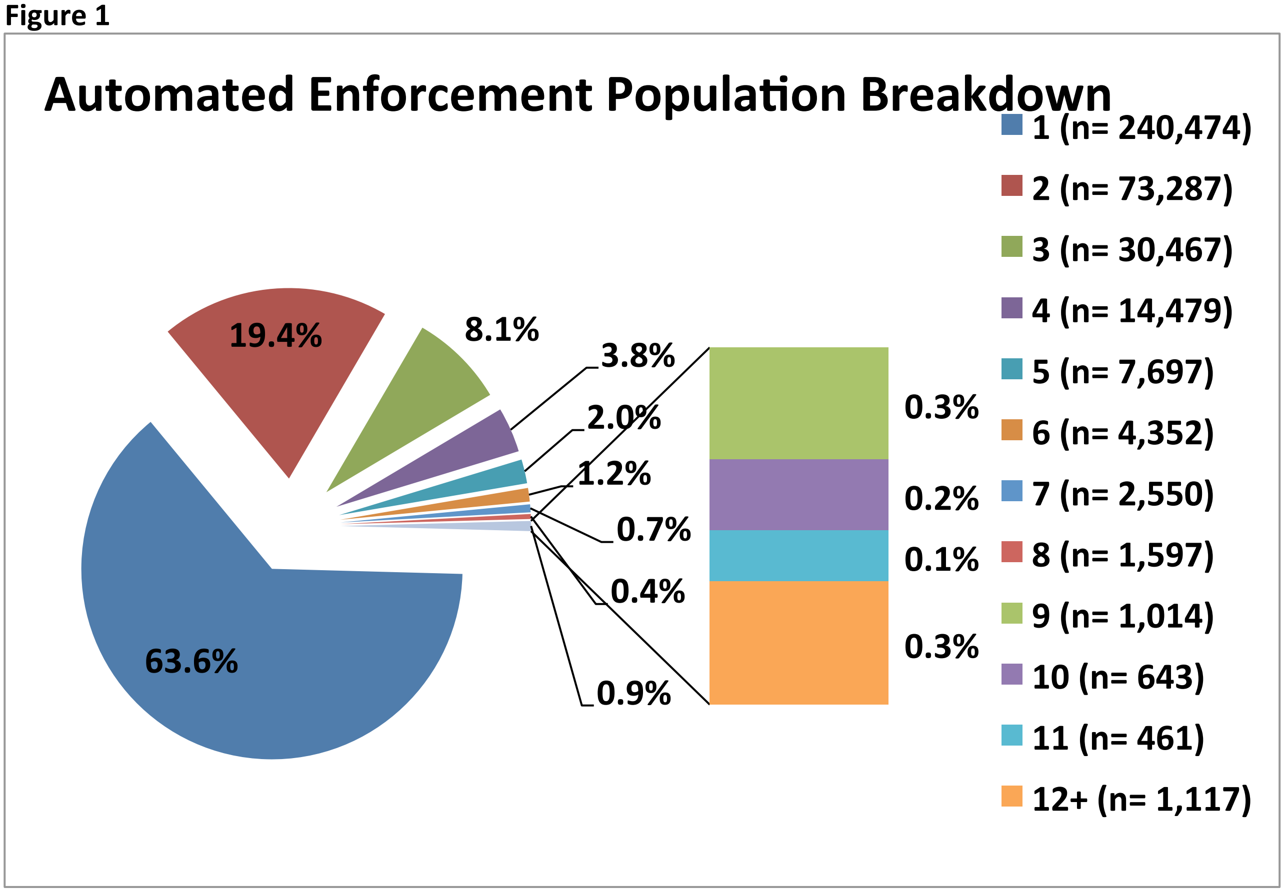


Figure 1 shows that the top violator groups compose a very small percentage of the total population of drivers with AE violations. For example, the 12+ violator category composes only 0.3% of the entire population, and accounts for less than 1% of the total collisions. Equally important is that the bulk (63.6%) of AE offenders have only one violation in a two year period, and that this same group accounts for a large proportion of all AE violator collisions which occurred in 2010/2011.

Figure 2 shows the percentage of vehicles in each offence category that were involved in at least one collision during the 2010-2011 period. Note that this does not take into account that certain vehicles were involved in multiple collisions in the same time period. For example, 17,549 of the 240,474 drivers with 1 AE violation (group 1) were involved in at least one collision in 2010-2011, meaning that 7.3% of the vehicles in group 1 were collision-involved.

Figure 2

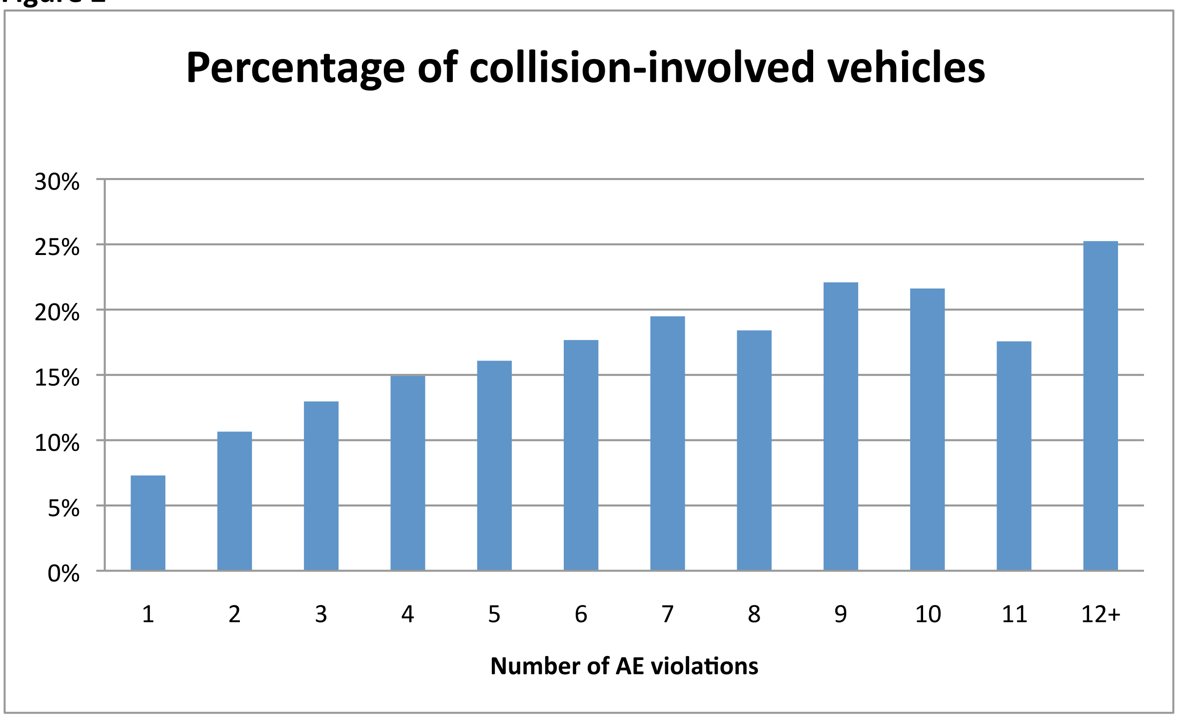
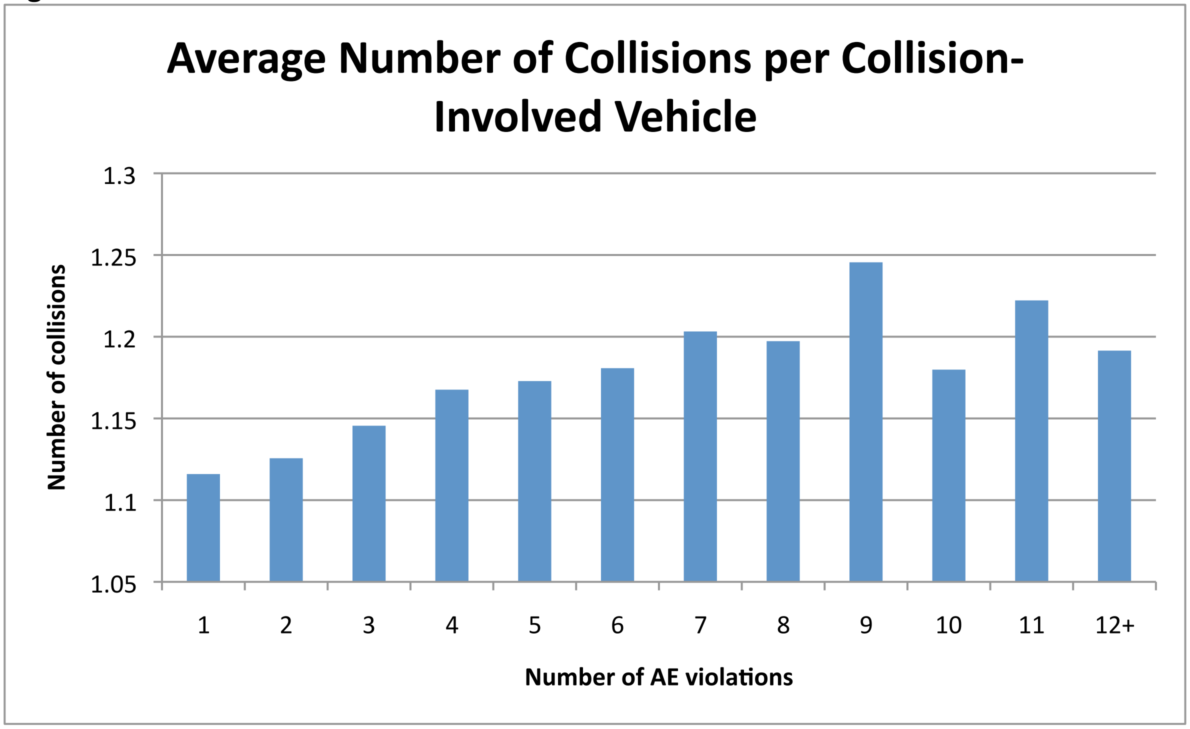


Figure 3 illustrates the total number of collisions per category divided by the total number of collision-involved vehicles in each category; in other words, it shows the average number of collisions per collision-involved vehicle, group by group. For example the collision-involved vehicles from group 1 accounted for a total of 19,584 collision involvements as some of the 17,549 vehicles had more than one collision involvement. This group of collision-involved vehicles, then, had an average number of 1.12 collisions per vehicle.

Figure 3



Both figures 2 and 3 show a positive relationship between the number of automated enforcement violations and overall collisions involvement. Figure 2 shows that the higher the number of automated enforcement violations, the higher the percentage of the group which was involved in at least one collision. The general trend is quite clear, though groups 8 and 11 indicate some deviation from the general pattern.

Figure 3 indicates that of the vehicles involved in collisions in the 2010-2011 period, those with more AE violations were also, on average, involved in more collisions. The relationship is quite clear from groups 1 to 9; though the average number of collisions in Figure 3 drops off somewhat for groups 10, 11, and 12+. The general relationship does not quite seem to hold for the higher violation groups in both Figures 2 and 3; this deviation from the trend cannot be explained given the current data, and could be a worthwhile focus for future studies.

Figure 4

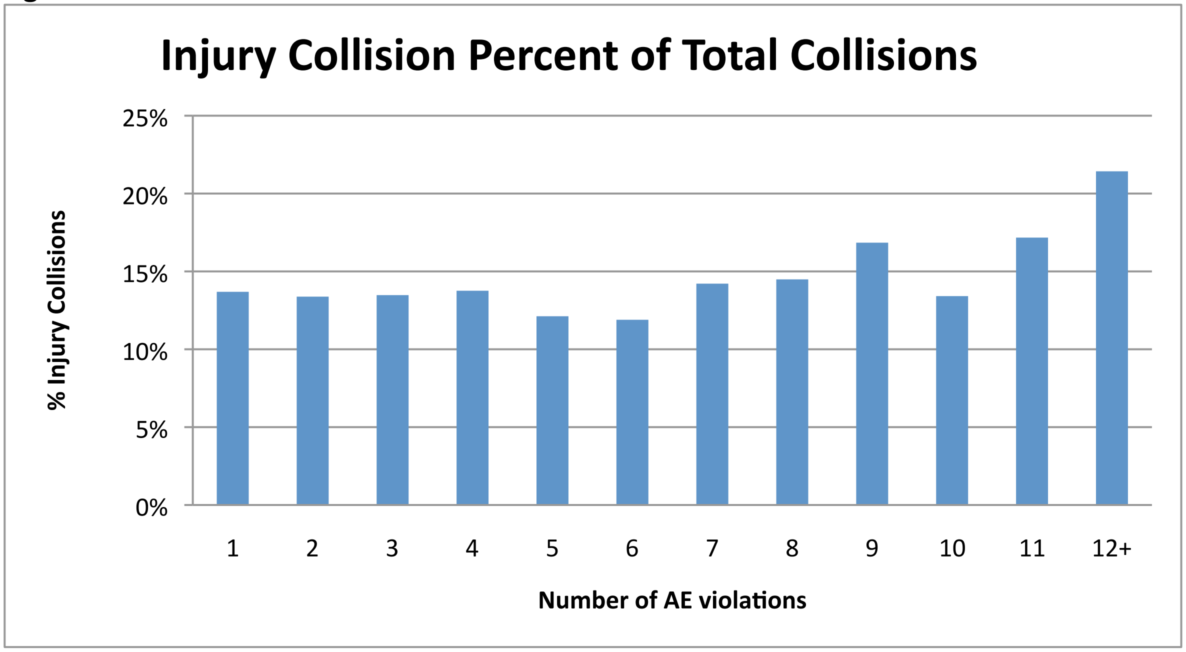


Figure 4 shows the percentage of collision involvements that were part of a collision event which caused injury to at least one person. For example, group 3 had 4,526 collision involvements in 2010-2011. Of those 4,526 collision involvements, 610 were part of injury collision events. This means that 13.5% of the collision involvements for group 3 took place as part of injury collision events.

The results of Figure 4 are somewhat difficult to interpret as the available data did not provide information on several important variables such as which driver is at fault or the number of vehicles involved in the collision event. What we can see is that the percentage of injury collision involvement fell between 12% and 17% with no discernible pattern for groups 1 to 11. Group 12+ saw a spike with 21% of collision involvements resulting in injury. While this study cannot explain why some groups have noticeably higher percent injury collision involvement, possible causal factors can be listed. These discrepancies within these groups could be explained by greater involvement of these groups in injury collisions with vehicles with no AE violations, or alternately from within the same group. Another possibility is that these groups may have a higher number of single-vehicle collisions.

Speaking more generally, the results of this section confirm the findings of related work on speeding and collision involvement. Chandraratna (2006) found that the more traffic violations and speeding offences a driver has, the higher the likelihood of culpable collision involvement. Cooper (1997) found that crash involvement was higher for drivers with greater numbers of speeding and non-speeding convictions. While the current study cannot identify which drivers were at fault in a collision event, nor draws a direct connection between non-speeding convictions and collisions, the current results certainly lend support to the findings that speeding is positively related to collision involvement.

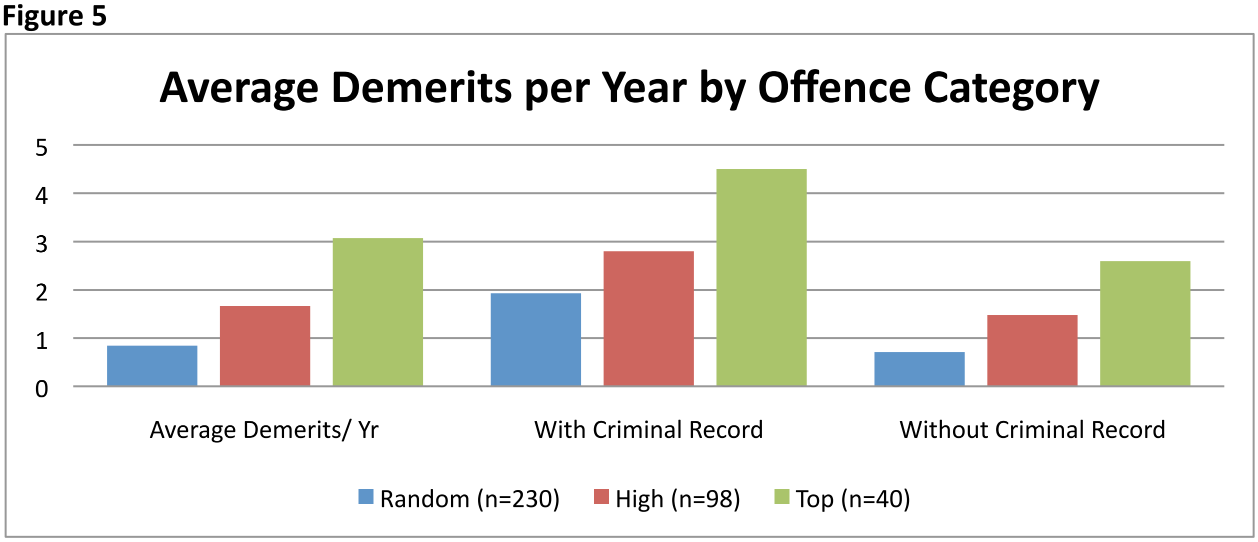
2) Demerits and Criminal History

This section is focused on determining the nature of the relationship between levels of automated enforcement violations and other traffic violations, as measured by driver record demerits. The possibility of a linkage between automated enforcement violations and criminal history is investigated, as well as evidence of driving while intoxicated. It should be noted that neither PRC nor ISD violations contribute towards a driver's total number of demerits; the only sanction for AE violations at this time is a monetary fine. As mentioned in the methodology section, the Random, High, and Top lists were selected on the basis of AE violations. The "Random" group was selected randomly from all vehicles with at least one AE violation in 2010-2011. The "High" group was randomly selected from all vehicles with twelve or more AE violations in 2010-2011. The "Top" group is composed of the 40 AE violators with the greatest number of AE violations.

Table 2

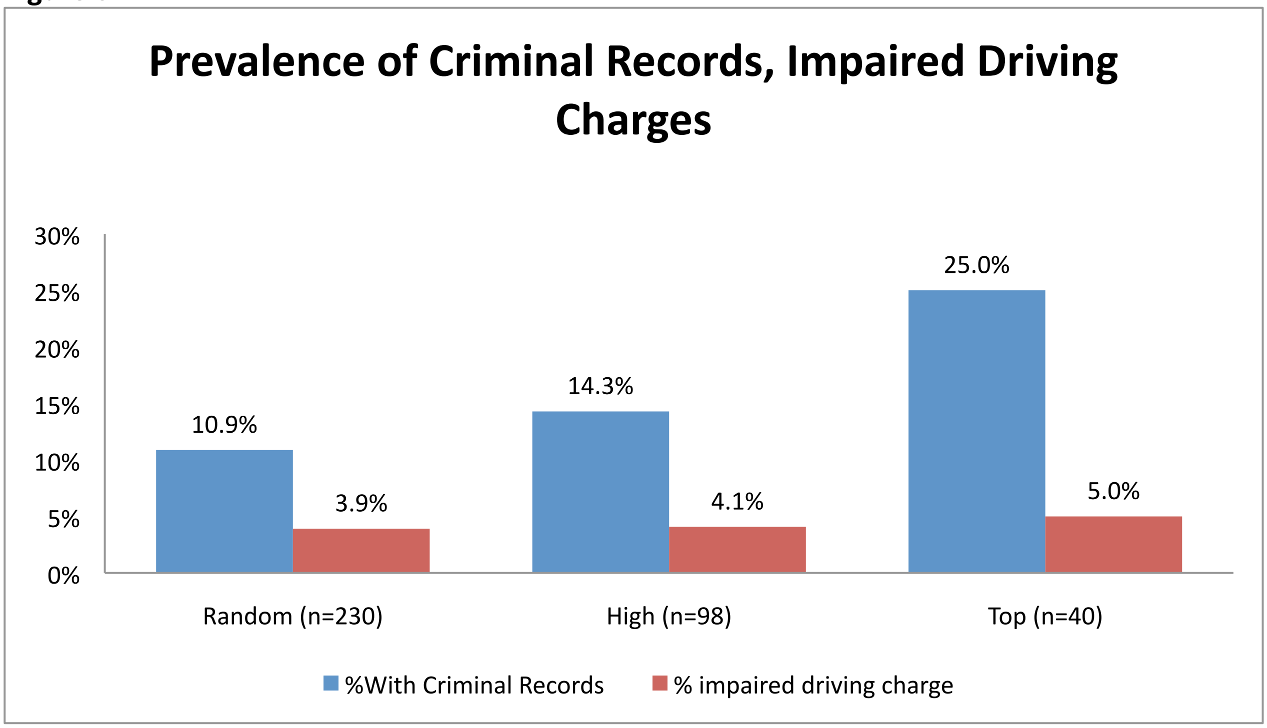
Category	Average Demerits/ Yr	%With Criminal Record	% Impaired Driving Charge	Avg Dem/Yr w/ Crim. Rec.	Avg Dem/Yr w/o Crim. Rec.	Avg AE violations in 2010-2011
Random (n=230)	0.84	10.9%	3.9%	1.93	0.71	1.7
High (n=98)	1.67	14.3%	4.1%	2.80	1.48	14.4
Top (n=40)	3.07	25%	5%	4.50	2.59	31

Figure 5



For Table 2 and Figure 5, the number of years an individual had been driving was calculated using the first entry on an individual's driver record as the assumed first year of driving. This made it possible to tally the total number of demerits accrued on the driver's record and subsequently calculate the average number of demerits each driver had per year. The approach is not ideal as it assumes that a driver will have been charged with a driving offence within the first year of driving which is rather unlikely. This may have the result that "better" drivers who receive less demerits may appear to have been driving for less time than they really have, as they are more likely to have gone several years driving without having accrued any demerits. Alternately, drivers who accrue a greater number of demerits- presumably by getting caught more frequently- are likely to have a more accurate number of years driving when calculated by this method. This is because their first violation is more likely to be closer to the actual date that they began driving. Assuming that driver behavior stays consistent over time, this method of determining the average number of years driving may result in low offending drivers appearing to have a slightly greater number of demerits per year than is actually the case.

Figure 6



In Table 2 and Figure 5, we can see that the Random group had a lower average number of demerits per year than the High or Top categories, with the Top category consistently having the highest number of average demerits. We can also see that drivers with criminal records had noticeably higher average number of demerits per year than those without criminal records in the same categories. Figure 6 shows that the Random group has the lowest percentage of drivers with criminal records (10.9%), while the High group has 14.3% and the Top group has the highest (25%). Impaired driving charges also increase slightly with the number of AE violations, though the change is so minimal that it may not be meaningful.

These findings suggest that there is a positive relationship between automated enforcement violations and other traffic violations. On average, those who committed more AE violations also committed more demerit-earning violations on the roadway. We also saw that increases in the number of AE violations went hand in hand with a larger portion of each group having criminal records. Drivers with criminal records, in turn, committed more demerit-earning violations than other drivers who had committed a similar number of AE violations.

These findings are in line with Broughton (2003) which found that drivers with a history of non-traffic offences were more likely to commit traffic offences than the general population. While the findings of the current study cannot suggest a causal relationship, drivers with criminal records certainly accrued a higher average number of demerit points than the other drivers in their group without criminal records. The current study also cannot explain why certain drivers are more likely to accrue more demerits or commit more AE violations. Palk (2005) proposes that low self-control may be the common factor behind drivers who repeatedly offend or have a general predisposition for risk taking. This in turn would be in line with Junger et al. (2001) which found a positive relationship between risky driving behaviour and traffic crime, a conclusion which closely mirrors the findings of this section of the current study.

3) Cross Jurisdictional

This section is focused on determining whether automated enforcement data can be used to identify broader patterns of driver behavior by looking across jurisdictions. The goal is to discover the extent of cross-jurisdictional traffic violations as visible via automated enforcement methods, and gain perspective on what population segment is committing cross-jurisdictional violations.

The total number of discrete vehicles that had any AE violations, either in Edmonton, Strathcona County or both was 378,138. The total number of vehicles with violations in both Edmonton and Strathcona County was 20,915. This means that 5.3% of all vehicles with automated enforcement violations had violations in both jurisdictions. For additional context, 15.2% of vehicles with two or more AE violations had violations in both jurisdictions.

Figure 7 shows the percentage of vehicles in each category which had violations in both jurisdictions. Figure 8 shows the total cross-violator population and the proportion the various violator groupings contribute to the whole.

Figure 7

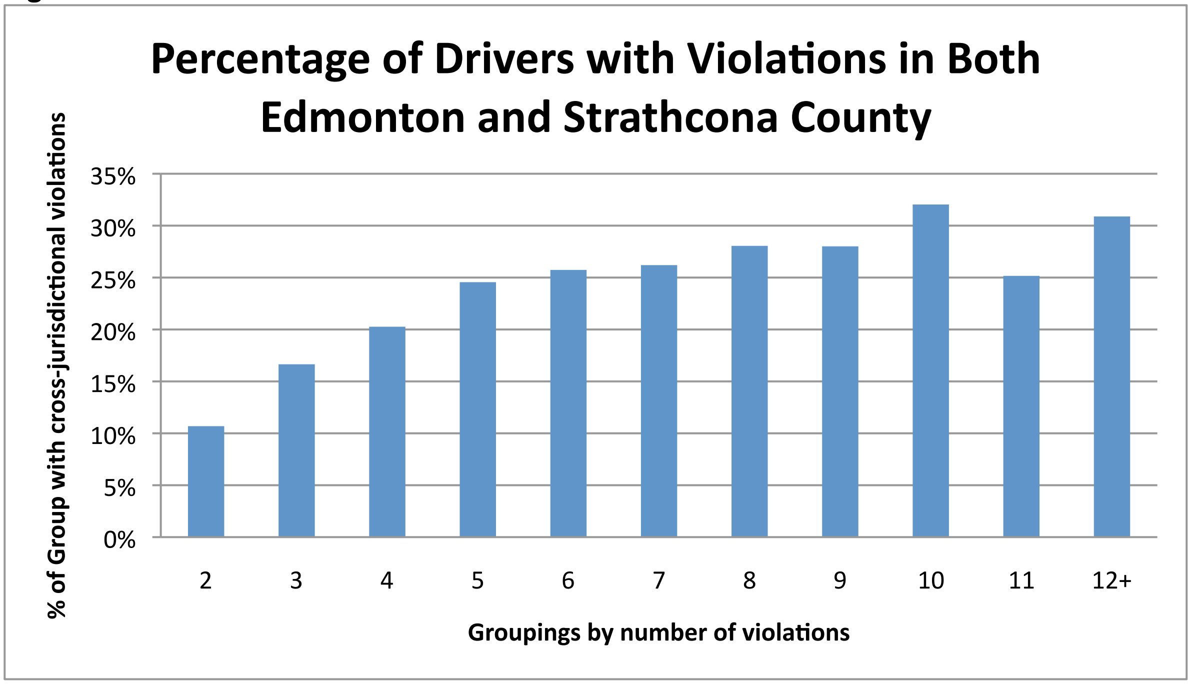
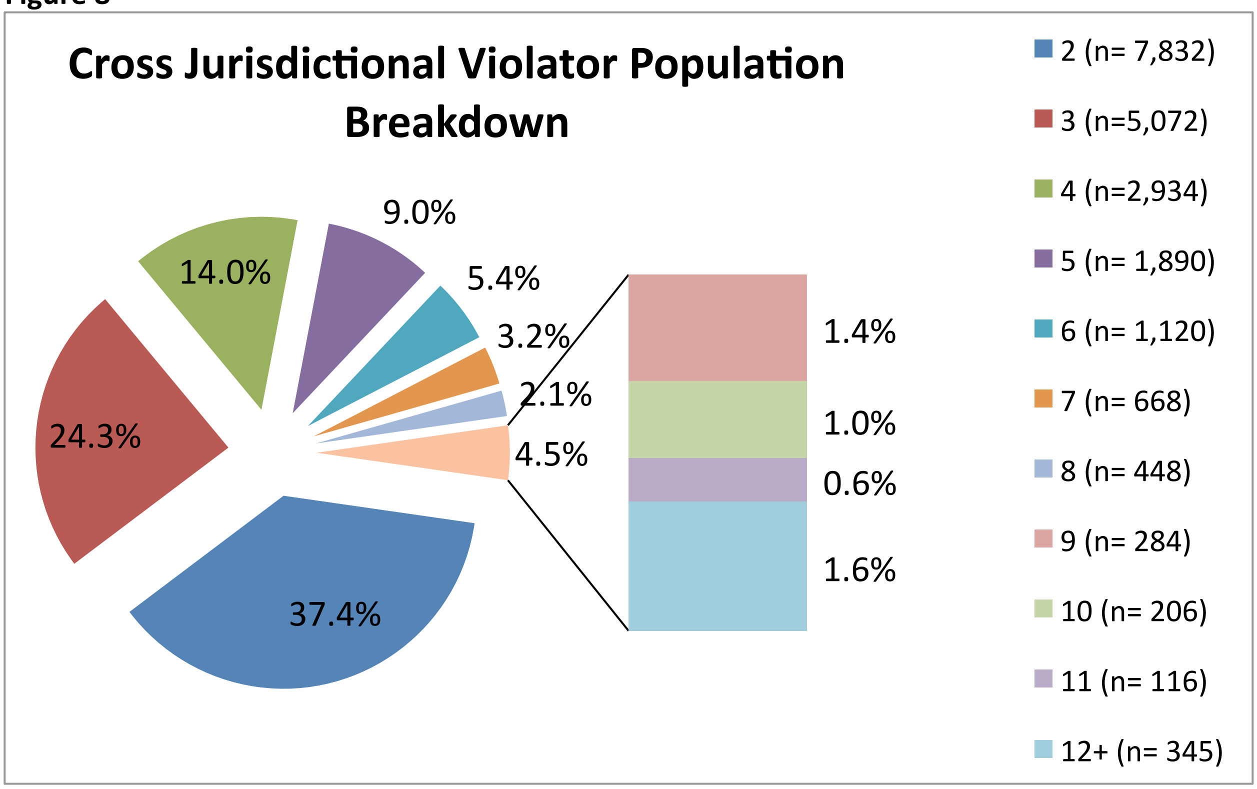


Figure 8



In Figure 7 there seems to be a general positive relationship between the number of AE violations and the prevalence of cross-jurisdictional violations. Group 11 represents a deviation from the general trend, however. Overall, group 2 has the lowest level of cross-juridisctional violations with a rate of 10%, while group 10 has the highest at 32%. Figure 8 shows that the highest number of cross-jurisdictional violators fall into the lowest violation grouping, and that for each additional violation the groups of violators continue to reduce in size. However, the highest proportions of cross-jurisdictional violation are found in the higher violator groupings.

These findings are somewhat difficult to interpret. Given that only 5.3% of all AE violators had cross-jurisdictional violations, it is possible that the majority of violators rarely drive outside of one jurisdiction, thereby making it much less likely that they would commit AE infractions in another jurisdiction. Alternately, drivers may be more cautious and more likely to obey the rules of the road when in a less familiar location. For drivers with an overall higher number of cross-jurisdictional violations, there are some interesting possible explanations. Some drivers may have the bulk of their violations in one of the two jurisdictional areas, which would suggest that even though they may not travel to the other area regularly, their driving habits remain similar regardless of location. Other drivers with higher overall violations may travel in both areas regularly and commit slightly less frequent violations in both. The benefit of a cross-jurisdictional view in this case is that what may appear as less concerning behaviour in both jurisdictions is suddenly seen as a more significant problem when data from both areas are combined.

V. Conclusions and Future Research

The first section of this study produced several key findings in its investigation of the relationship between AE violations and collision involvement. Three general trends emerged from the data: First, there is a strong, positive relationship between AE violations and collision involvement. In other words, groups with higher levels of AE violations had a greater proportion of vehicles involved in collisions. Second, vehicles that were collision-involved and that had a higher number of AE violations were also involved in a higher average number of collisions. Third, the group with the highest number of AE violations had a noticeably higher injury collision involvement rate than the other groups.

The second section of the study- which explored the relationship between AE and non-AE traffic violations as well as criminal involvement- also produced meaningful results. The first was that drivers who committed more AE violations also committed more demerit-earning violations on the roadway. The second was that criminal history varied alongside both the number of AE and demerit-earning traffic violations; the group with the least violations and demerits had the lowest percentage of drivers with criminal history while the group with the most violations and demerits had the highest. The third finding was that drivers with criminal records had a noticeably higher average number of demerits than other drivers from the same groupings without criminal history.

The third section of the study focused on AE violations across jurisdictions. This section also returned worthwhile findings. The first finding was that only 5.3% of all drivers with any number of AE violations had committed AE offences in both jurisdictions. The second finding was that drivers with a higher number of AE violations were more likely to have offended in both the City of Edmonton and Strathcona County in 2010-2011.

In light of these findings, it seems fair to acknowledge that automated enforcement data shows significant promise as a means of identifying at least a portion of the high-risk driving population. For instance, a quarter of the 12+ violation grouping was involved in at least one collision in 2010-2011. Of those collision involvements, twenty percent saw at least one injury during the collision event, an injury rate noticeably higher than any other group of drivers in this study. These same drivers accrued twice as many driving demerits per year as the average AE offending driver, suggesting much higher overall rates of traffic violation. Roughly a third of the group had AE violations in both jurisdictions which were studied. Last but not least, given that these vehicles are in the 12+ grouping, they are associated with at least 12 speeding or red light running offences in only two years, though the most prolific offender had 40 in that same time period.

These numbers certainly paint a troubling picture. Effective intervention within this group could potentially prevent collisions, making the road safer for all. This leads to some difficult questions, however: How best to intervene? What resources are acceptable to expend on this problem? What is an "acceptable" level of AE violations? At what level of AE violation is action necessary? What drivers are dangerous but invisible to AE methods?

The greater context in which these drivers are operating is also important. The 12+ violation group is composed of 1,117 vehicles, responsible for 336 collisions. The 1 violation group alone is composed of 240,474 vehicles, and is responsible for 19,584 collisions. Are resources better spent on the individually riskier minority, or the individually safer majority that accounts for thousands more collision involvements per year?

One thing is certain: a reduction in collisions is a laudable goal. To achieve this goal, more research is needed. To follow up on this study, the discovery of more refined methods of identifying high-risk drivers could in turn lead to more effective intervention methods. Future research which integrates speed data could be useful to this end. Factoring in demographic factors and other driver attributes in conjunction with AE violation behaviour could lead to the development of a predictive tool which could be used by law enforcement agencies.

To summarize, the findings of this study indicate that automated enforcement data can be used to provide valuable insight into driver behaviour. Automated enforcement data show significant potential as a tool to identify a portion of the high-risk driver population. It further provides insight into overall driver behavioural trends, which is further improved when data is combined across jurisdictions. Given the promising findings of this initial study, the topic merits further research.

VI. REFERENCES

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