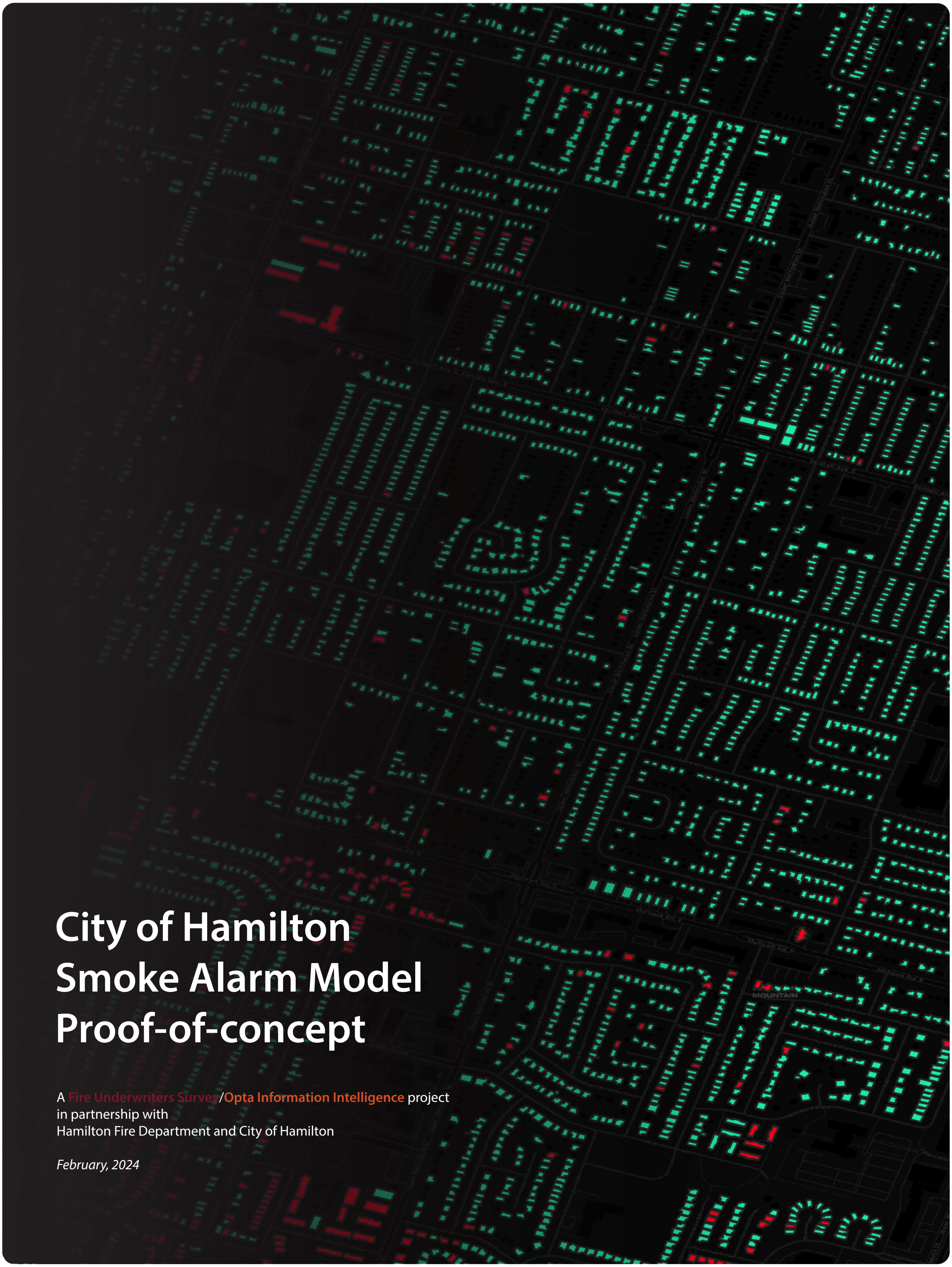

# City of Hamilton Smoke Alarm Model Proof-of-concept

A Fire Underwriters Survey/Opta Information Intelligence project
in partnership with
Hamilton Fire Department and City of Hamilton

*February, 2024*

# City of Hamilton Identification of Non-working Smoke Alarm Model Proof-of-concept

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## Fire Underwriters Survey/Opta Information Intelligence team

Robert McGuinness P.Eng. – Project Lead (robert.mcguinness@verisk.com)
Leon Zhong – GIS Architect (yi.zhong@verisk.com)
Zakary Whittamore – Data Scientist Team Lead (zakary.whittamore@verisk.com)
Greg Gilbert – Head of Data Science (greg.gilbert@verisk.com)
Filip Stojanovic – Data Scientist

## Fire Department and Municipal Partners

We would like to thank the Hamilton Fire Department (HFD) and the City of Hamilton for contributing to this report. Without their generous participation and support this project would not have been possible. Of particular note, we would like to thank the following: Fire Chief David Cunliffe; Deputy Fire Chief John Verbeek; Yvette McCormick, Division Chief of Administration; Helen Klump, Manager Strategic Initiatives; Karen Danner, Administrative Assistant; Mark Mitchell, GIS Technologist.

## Disclaimer

# Summary

"…**42%** of all non-working smoke alarms are found in properties with the highest model **Risk Scores.**"

Statistics Canada reports that in 2021, of the 202 fire-related deaths, three out of four occurred in residences. Among the 10,819 residential fires, 1% ended in a death, with a total of 156 fatalities. Just over one in three residential fires had a working smoke alarm. Death rates were lower in homes with working smoke alarms, where 26% of incidents resulted in death. Homes without a working smoke alarm, including those without an installed alarm, or the status is unknown, accounted for nearly three out of four deaths (74%). [1]

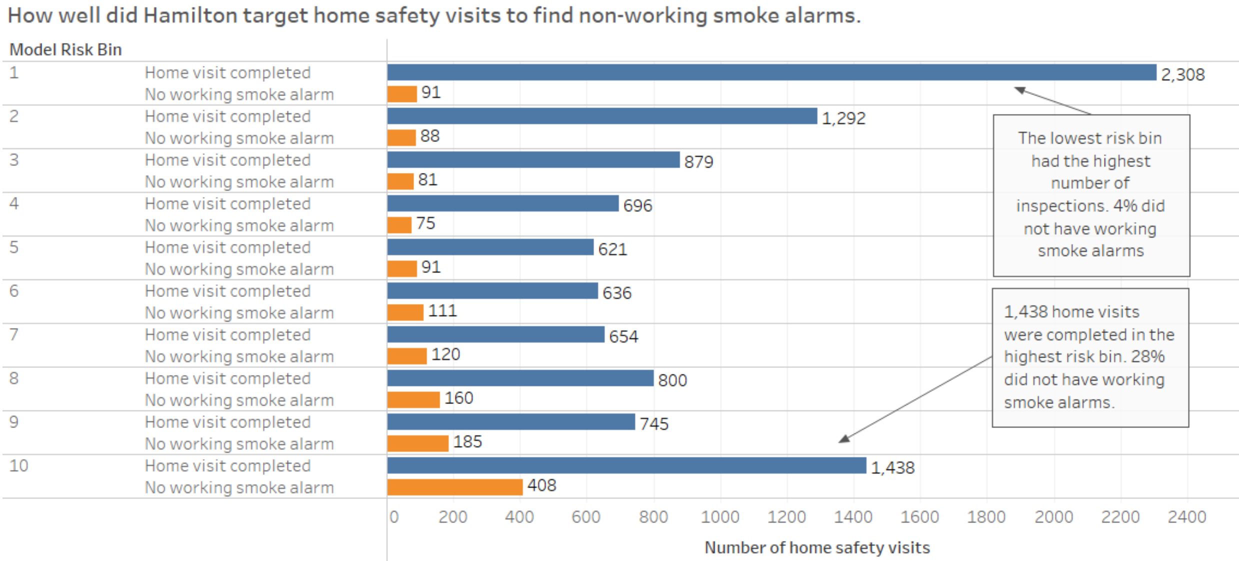
Hamilton Fire Department (HFD) completes home fire safety visits to ensure there are working smoke alarms in residential properties. HFD finds that approximately 18% of properties visited do not have working smoke alarms. However, in residential fires in the City of Hamilton the proportion that do not have working smoke alarms is much higher at approximately 50%. [2]

This proof-of-concept (PoC) project looks at using a machine learning approach, previously applied to inspectable properties [3], to identify residential properties without working smoke alarms. HFD provided home fire inspection data for the period 2017-2019. The data was split for training and testing. The results of the model test are shown in figure 1. 42% of all non-working smoke alarms in the test data are found in the highest model risk bins/scores (shown as 9/10 in figure 1).

Figure 1 Hamilton smoke alarm model test summary

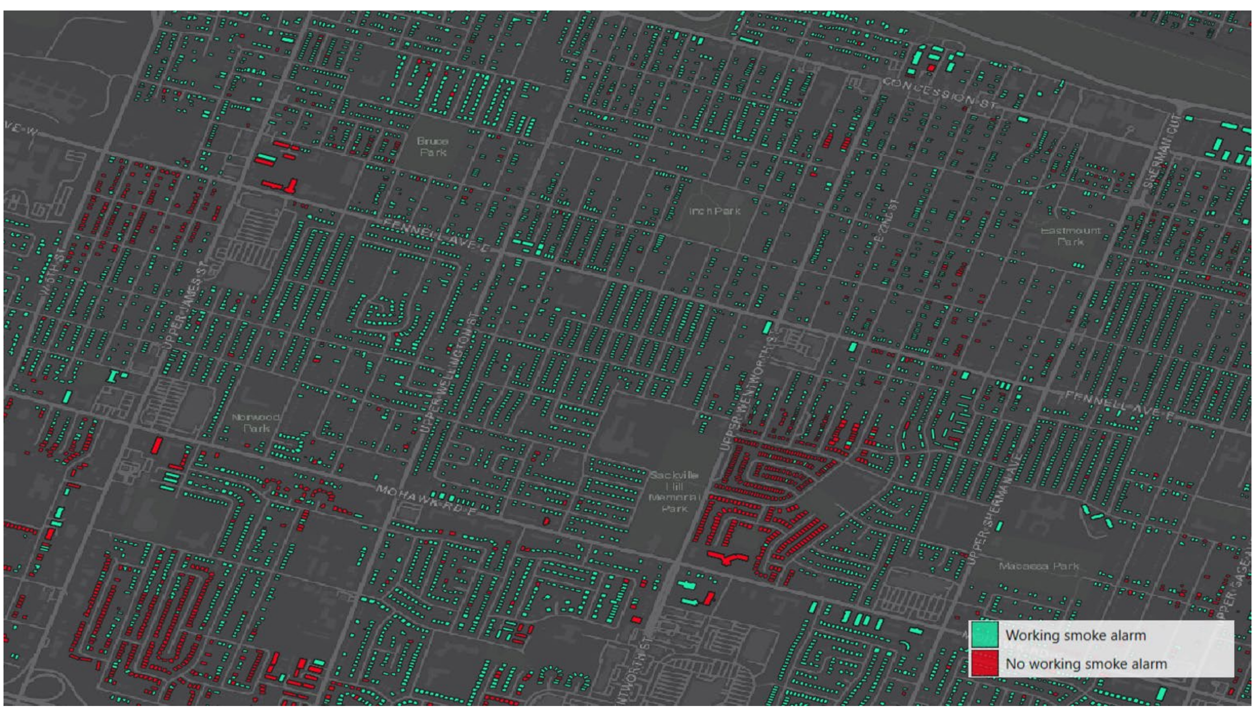

Figure 2 shows a summary of all the home inspections completed by HFD. The model prediction bins are also shown (9/10 are higher likelihood of non-working smoke alarms). HFD completed the highest number of inspections (2,308) in the lowest risk bin and found 91 homes in this risk category without a working smoke alarm, i.e., 4% of home visits found a non-working smoke alarm. 1,438 inspections were completed in the highest risk bin (10) and found 408 non-working smoke alarms, i.e., 28% of visits found a non-working smoke alarm. Targeting properties in the highest risk bins (9/10) would be expected to find more properties without working smoke alarms. Ensuring more working smoke alarms in more homes has an impact on the frequency and severity of residential fires based on the literature reviewed in this report. [4]

Figure 2 Targeting of homes with non-working smoke alarms.




An overview of the model prediction scores is shown in figure 3. Properties in risk bins 9 and 10 are coloured red.

Figure 3 Hamilton model scores



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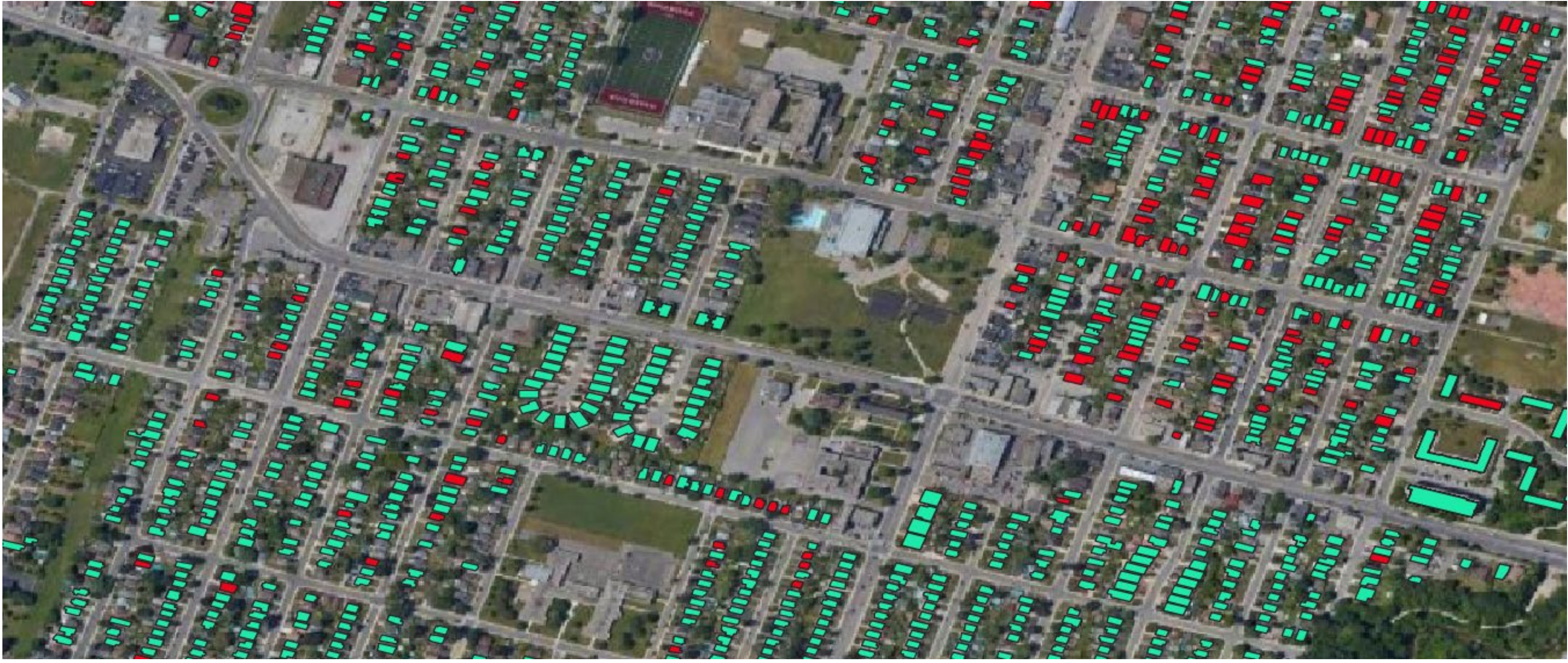


# Introduction

## Overview of prevention

"...of the 202 fire-related deaths, three out of four occurred in residences. **Just over one in three residents have a working smoke alarm.**" ... (Statistics Canada).

Municipal fire departments in both Canada and the US have a fire prevention division tasked with reducing preventable fires. Fire prevention inspections are generally completed only for "public" buildings [5] which include:

> *"hotel, public building, church, theatre, hall or other building used as a place of public resort" (BC Fire Services Act Part 2, 36 (1))*

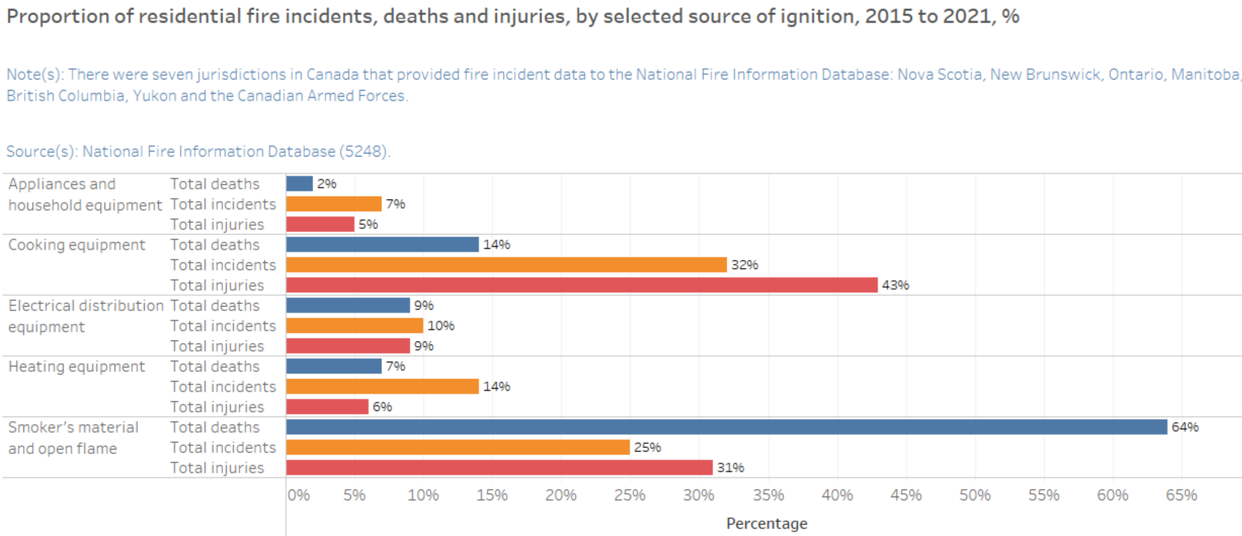
In some jurisdictions, the fire prevention inspections are completed on a regular frequency set by the municipality (e.g. annually), in other jurisdictions the inspections are based on complaint/request without a regular frequency. Fire prevention inspections generally do not apply to residences. The issue of residential fires is generally addressed through public education which is normally a sub-unit of the fire prevention division. Some communities complete more targeted residential fire safety programs.

Statistics Canada publishes fire related data from the National Fire Information Database project and note that residential fires account for the most fire deaths [1]. From Statistics Canada:

> *"In 2021, of the 202 fire-related deaths, three out of four occurred in residences.*
>
> *Just over one in three residents have a working smoke alarm.*
>
> *From 2015 to 2021, 37% of residential fires had a working smoke alarm, while 12% had smoke alarms that did not activate and 13% had no smoke alarm installed.*
>
> *Death rates were lower in homes with working smoke alarms, where 26% of incidents results in death. Homes without a working smoke alarm, including those without an installed alarm of the status is unknown, accounted for nearly three out of four deaths (74%)."*

With the population of Canada at approximately 35 million in 2021, this gives a fire-related death rate of 202/35 = 5.8 per million. In 2022, the Office of the Fire Marshall reported fire-related deaths at 125 [6]. With the population of Ontario at approximately 15 million in 2022, this gives a fire-related rate of 125/15 = 8.3 per million. It should be noted that in general fire incidents increased during the pandemic [1]. Statistics Canada further breaks down residential fires by the ignition source as shown figure 2 below. Smoking and open flames are the ignition source in 64% of fire deaths; cooking equipment is the ignition source in 43% of injuries.

Figure 4 Summary of residential fire incidents from National Fire Information Database (source Statistics Canada).




## Overview of residential fire safety concepts

> "...fire service is visiting large numbers of households to ensure they have a working smoke detector. **The approach is thought to be a major factor in the 40 percent drop in fire deaths**...(Global concept in residential fire safety)."

In 2007, the National Centre for Injury Prevention and Control within the Centers for Disease Control and Prevention (CDC) released Part 1 of a study on Global concepts in residential fire safety. The first phase focused on practices in England, Scotland, Sweden and Norway [7]. The summary of the report notes the following:

> *"Of all the best practices identified in this study, one stands out. To reduce fire causalities in the home, the British fire service is visiting large numbers of high-risk households to do fire safety inspections and risk reductions, especially to ensure they have a working smoke detector. This approach is thought by the British to be a major factor in the 40 percent drop in fire deaths in the United Kingdom over the last 15 years, and it probably could have a large impact in the United States and other nations as well."*

The best practices from the UK fall into eight categories which include: risk analysis to identify high-risk households; increasing staffing and training in prevention programs; extensive home fire safety visits; national and local fire safety campaign; extensive school and youth programs; programs for high-risk elderly populations; developing safer consumer products; using fire stations for community fire safety programs.

The home fire safety visits go beyond solely installing and testing smoke alarms. The visits include one-on-one education and inspection and mitigation of hazards. The visits can be supported by a community safety specialist and are often scheduled after referrals from social services or other agencies. The report notes that Norway and Sweden both complete home fire safety visits.

In Canada, multi-family residential/apartment buildings generally fall under inspectable properties (Major occupancy classification C – residential [8]). As part of a fire prevention inspection, only the common property space ("public") will get inspected. Fire safety for apartments in the building is not generally addressed as part of the inspection. Many fire prevention divisions point this out as an issue. The CDC report discusses how Oslo Fire Brigade tries to enhance their fire safety program for these types of buildings:

> *"The Oslo Fire Bridge annually visits all of its old, high-risk apartment buildings to meet with occupants to discuss fire safety. Posters in the building advertise when the fire service is coming. Oslo condominium associations are given safety checklists to pass on to unit owners."*

Examples of developing safer products for the home are portable home sprinkler systems for extreme high-risk households - UK; timers being built into stoves or connected to stoves to shut off the stove if the person cooking forgets to do so or falls asleep (advocated especially for households with elderly) – Norway. Norway also requires extinguishers in every home and home occupants are trained to extinguisher small fires. London Fire Brigade promotes portable protective systems (PPS) and flame-retardant bedding through their home fire safety visits [9].

## Residential fire safety concepts in Canada

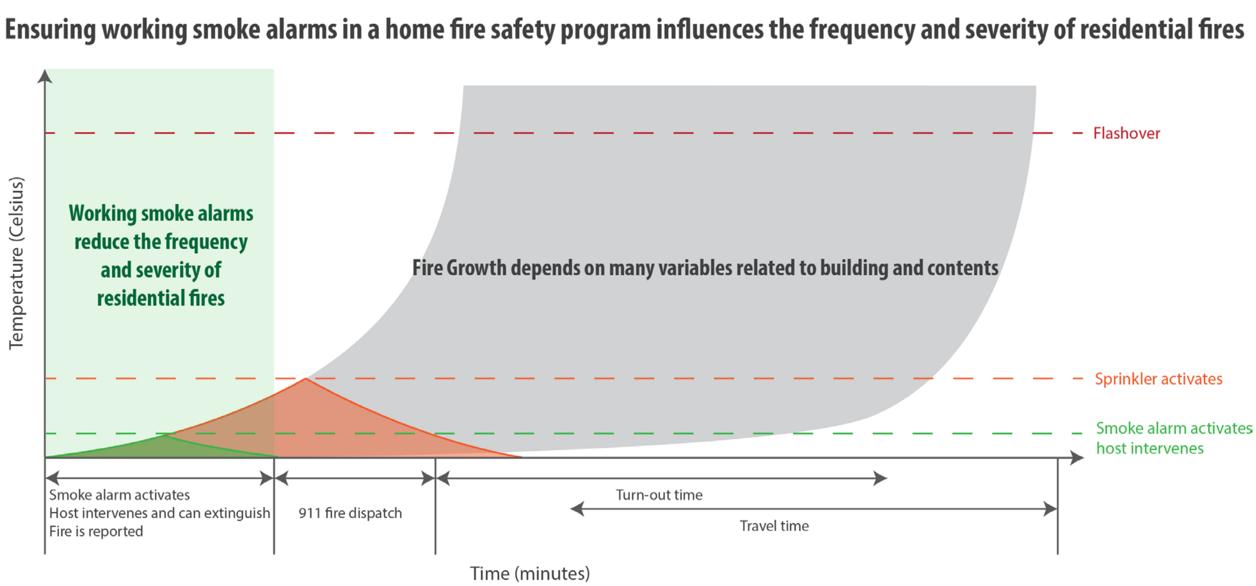
"…home fire safety visit had an impact on the frequency and severity of residential fires…(Surrey study, Journal of Fire Safety Research)."

In 2008, Surrey Fire Services began a study to investigate the impact of home fire safety visits on frequency and severity of fires [4]. 18,473 home visits were completed, and the study found that the home fire safety visit had an impact on the frequency and severity of residential fires. Each home visit was approximately 5 minutes and focused on basic education around cooking and non-smoking related open flames as well as a smoke alarm test. If a smoke alarm was not present the firefighters would offer to install a free smoke alarm.

In 2009, the National Centre for Injury Prevention and Control within the Centers for Disease Control and Prevention (CDC) released Part 3 of a study on Global concepts in residential fire safety. This phase focused on Canada, Puerto Rico, Mexico, and Dominican Republic. The report talks about home visits and notes that many Canadian fire departments do home visits on a large scale with the plan of visiting all households over a specified time period (e.g. five years). However, having surveyed many Canadian fire departments over the past 15 years, we have found that these home fire safety visits are not necessarily completed as suggested in the CDC report. However, the report does mention specific cases of home fire safety visits in Longueil, Ottawa, and Brampton.

In recent years, there has been more focus on community risk assessment and risk reduction in Canada. In 2017, Regina Fire & Protective Services, with the University of Regina, completed a research report on "Incidence, Circumstances and Risk Factors of Residential Careless Cooking Fires in the City of Regina" [10]. The report further investigates the factors that affect the severity of a residential cooking fire and focuses on the 'host' characteristics such as demographics; major act of omission; location at time of incident (e.g., unattended cooking); host intervention, mitigation, extinguishment behaviours. The work looks at the 'human factors in fire' concepts [11] to help direct fire prevention activities. Of the 884 (432 in 2014 and 452 in 2015) cooking fire incidents that the Fire Department responded to and reported on, they found that more than half of the hosts were alerted to the incident by their smoke alarm. Most of the hosts attempted intervention and the study highlighted the importance of a working smoke alarm in predicting timely host intervention to prevent or mitigate the effects of a cooking incident, reducing the need for firefighter's intervention and the severity of the incident. Statistics Canada report from the National Fire Information Database project [1] found that firefighters account for nearly one in five persons injured during a fire. Figure 3 illustrates how a working smoke alarm can have an influence on a fire propagation curve.

Figure 5 Host intervention in fire outcome as a result of working smoke alarms



Based on the work mentioned here, it would be beneficial to target homes that are more likely to not have working smoke alarms. Statistics Canada and the BC Office of the Fire Commissioner released a community risk reduction dashboard to help target home fire safety programs in 2022 [12].

### Prioritizing home visits in the City of Hamilton

"HFD continues to find a large number of residential fires (almost 50%) that do not have working smoke alarms."

Hamilton Fire Department continues to find a large number of residential fires (almost 50%) that do not have working smoke alarms [2].

Hamilton Fire Department has a home fire safety inspection program and provided 20,109 inspection records for the period January 2017 to March 2019. The data tracks 'Access' with the possible values: "No One Home", "Access Granted", "Access Denied". In 4,230/20,109 (21%) cases, access was denied. In 9,348/20,109 (47%) cases there was nobody home. In the remaining 6,526 cases access was granted and the Fire Department was able to enter the home to confirm if there was a working smoke alarm. In 2,155 of the cases where access was denied, HFD was still able to confirm the status of the smoke alarm. In total, the presence of a working smoke alarm could be confirmed in 8,677 cases with 82% of homes having a working smoke alarm.

In 2019, a validation project was completed with the City of Vancouver and City of New Westminster to test methods used by New York City [13], the City of Atlanta [14] and the City of Pittsburgh [15]. In each of these municipalities the work showed that a data-driven risk-based approach proved to be better at targeting risks than previous practice (source A Building Fire Risk Prediction Validation Project [16]). It may be beneficial for the reader to review "A Building Fire Risk Prediction Validation Project" as it covers previous work in data-driven approaches to fire risk assessment. HFD wanted to investigate using this same targeting approach to better identify homes without working smoke alarms.

This project, originally completed in 2020, looks at using a machine learning approach to target home fire safety visits with HFD. The approach allows the Fire Department to continually update the model based on the most recent inspection data.

## Methodology and Model Results

### Datasets

A summary of the Hamilton Fire Department home fire safety inspection program is shown in figure 6. The data captures whether there was a working smoke alarm or not. In cases where the inspection could not confirm, the presence of a working smoke alarm is captured as "unknown". The summary is only shown for cases where the presence of a smoke alarm could be confirmed. Fire Station 16 completed the greatest number of visits at 1,144. 15% of the homes visited did not have a working smoke alarm. Fire Station 18 has a high identification rate at 50%; however, only 121 home visits were completed. Overall, the success of finding homes without working smoke alarms is 18% (1,525/8,677).

We used the home fire safety inspection program data along with other datasets (see table 1) to build and test a model to identify homes without working smoke alarms.

Figure 6 HFD fire safety inspection program summary

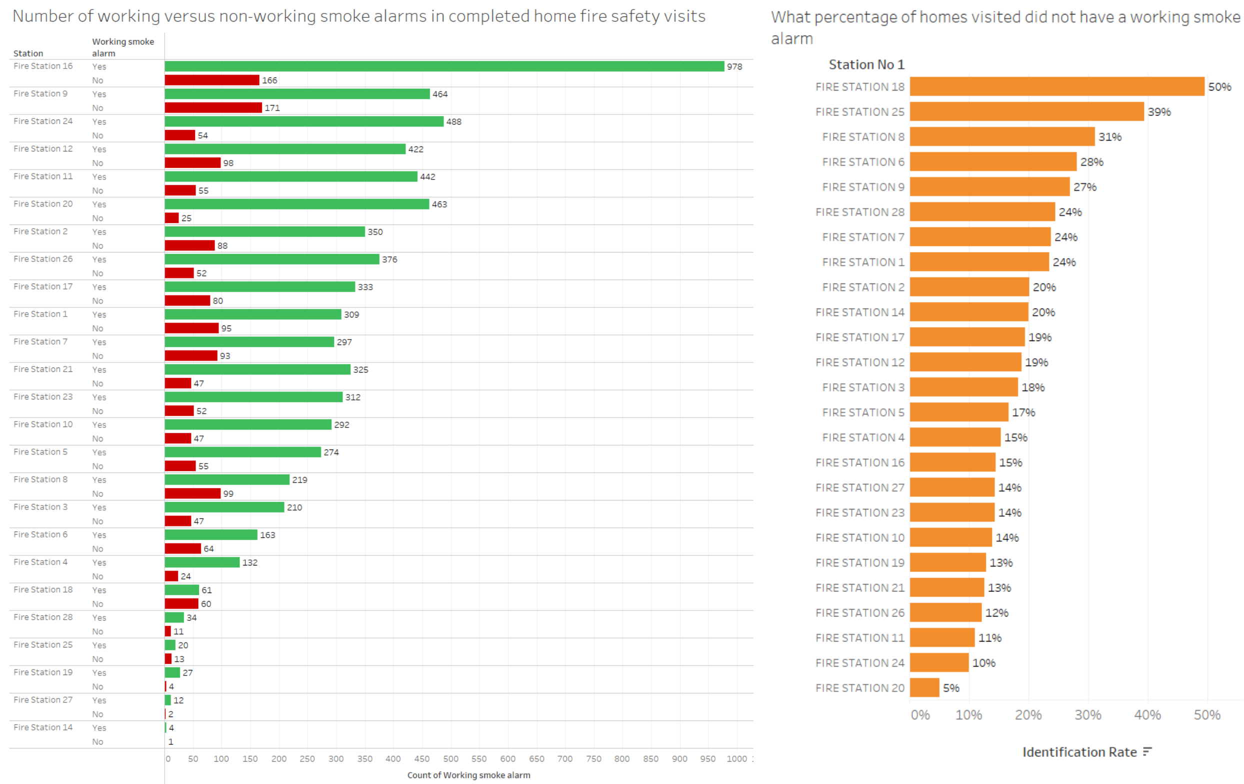



Table 1 Hamilton Municipal Datasets

| | *Records* | *Fields* | *Source* | *Description* |
|---|---|---|---|---|
| **PARCEL_ASSESSMENT.shp** | 173,143 | 6 | Hamilton Fire Department | Parcel data |
| **BUILDINGS.shp** | 201,154 | 7 | Hamilton Fire Department | Building footprints |
| **LU_PRIM.shp** | 17,576 | 3 | Hamilton Fire Department | Landuse data |
| **ADDRESS_POINTS.shp** | 248,786 | 8 | Hamilton Fire Department | Address data |
| **Fire Home Safety Education Program.xls** | 20,109 | 9 | Hamilton Fire Department | Home inspection data |

## Data Cleaning and Joining

A GIS approach was used to cross reference data. The Fire Home Safety Education Program data was provided in an excel format with address fields. We built our Locator address dataset base layer from the ADDRESS_POINTS dataset. The Locator was then used to spatially join the Fire Home Safety Education Program data. From https://pro.arcgis.com/en/pro-app/help/data/geocoding/about-locators.htm:

> *"Locators provide specialized indexes, rules, configuration, and regional knowledge that allow a more sophisticated approach to search, as opposed to only performing a database query."*

This GIS approach is a better alternative for joining datasets at the address level especially as other database keys are not available in the Fire Home Safety Education Program data. It also aids in joining addresses that have slight user input variations.

The ADDRESS_POINTS data is used as the main aggregation level and all other data is connected to this layer using a unique address key. Addresses can be stored in multiple variations, and it is common for municipalities to run into congruence issues across data applications. It is expected that various civic addresses in the Fire Home Safety Education Program data are likely not recorded in the same format as the ADDRESS_POINTS data. The geocoding process scores the match from 0-100. Generally, a score of >=80 is considered a reasonably good match. For example, an address like "71 MAIN ST N, FLAMBOROUGH" from the Fire Home Safety Education

Program data matches to “71 MAIN STREET NORTH, FLAMBOROUGH, HAMILTON, ONTARIO, L8N L8N1G2” with a score of 89.94 in the Locator.

However, an address such as “144 EWEN RD, HAMILTON, ON” in the Fire Home Safety Education Program data does not match to any address in the ADDRESS_POINTS data. 484/20,109 (2%) of addresses could not be matched.

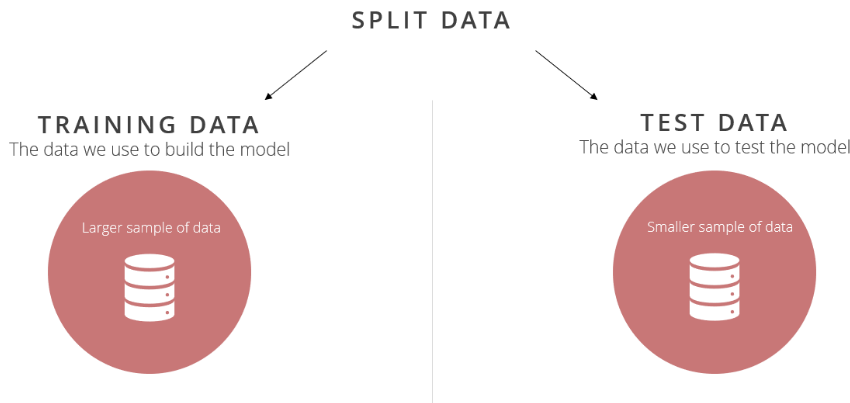
Once the datasets had a reference ID, the raw data fields were mapped to standardized internal fields for modeling and the data further aggregated to prepare the model.

## Prediction Model Results

In the Fire Home Safety Education Program, there is a field called “Smoke Alarms Compliant?”. We built the model to identify when this value is listed as “No”.

The data was split into a test and training sets as illustrated in figure 7.

Figure 7 Training and test datasets

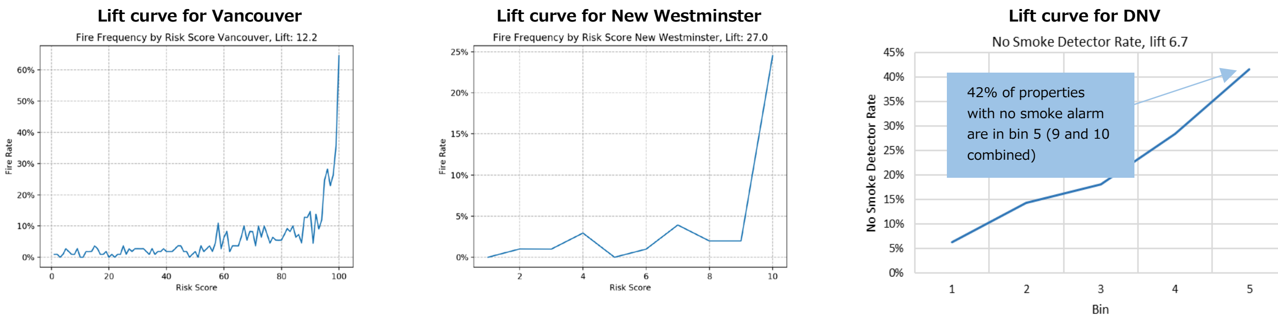



The final product of the model is a “risk score”, built by uniformly binning the data on the output probability of the logistic regression for binary classification. In other words, we evenly distribute properties into 10 bins/categories/scores (based on the probability) and then look at how many of the properties in the higher bins (9 and 10) had fires compared to those in the lower bin (lift analysis). The results are provided in a visualization (figure 8) and a general overview of model performance using lift analysis (figure 9). Model validation metrics follow. The City of Vancouver and City of New Westminster are provided alongside for comparison (source A Building Fire Risk Prediction Validation Project [3]); however, note that these model targets are different from the Hamilton project.

A lift curve can help measure the effectiveness of a predictive model and is calculated by taking the number of relevant events predicted at a given risk score over the total number of events assigned to that score. Figure 8 shows the lift curves for Vancouver, New Westminster and the City of Hamilton.

In all cases the frequency of target events increases in the top quintile of risk scores/bins compared to the bottom quintile. This can be measured by the lift (defined as the fraction of average fire frequency in the top quintile of scores over that in the bottom quintile). Vancouver experiences a lift of 12.2, New Westminster a lift of 27 and the Hamilton model a lift of 6.7.

Figure 8 Lift curves for risk scores/bins




"…**42%** or properties without a working smoke alarm are in the **higher risk bins (9/10)**."

The lift curve for the Hamilton model shows that 42% of properties without working smoke alarms are in Bin 5 (joined bins 9 and 10, see figure 9). 6% of properties without working smoke alarms are in bin 1 (joined bins 1 and 2, see figure 9). In figure 9 below, the colours represent the model predictions, i.e. red predicts higher likelihood of non-working smoke alarm, green indicates lower likelihood of non-working smoke alarms. The size of the circles shows what the home inspection actually found. Large circle shows that the Fire Department found a non-working smoke alarm and the small circles indicate a working smoke alarm. Large red circles and small green circles indicate model prediction agreement with actual inspection. There are a larger number of large red circles than large green circles. Also, the majority of the small circles are green.

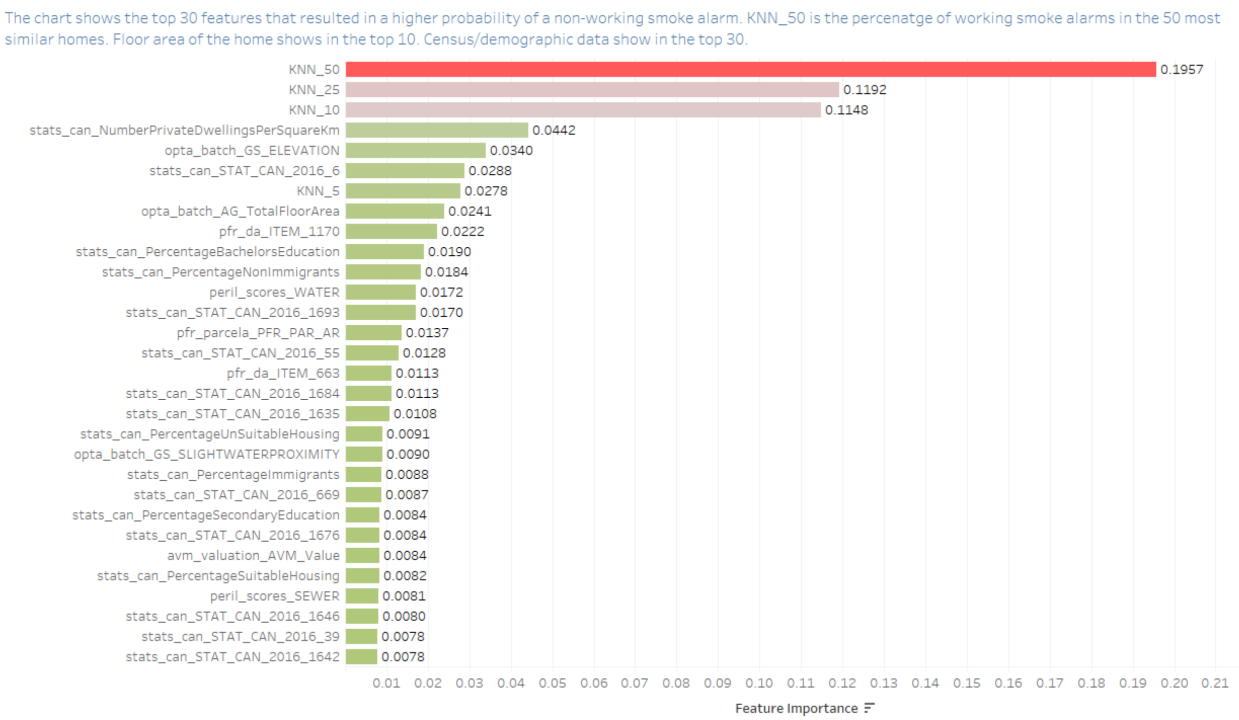
Figure 9 Smoke alarm model summary

## Model Feature Importance

The model feature importance is shown in Figure 10. The chart shows the top 30 features that resulted in a higher probability of a non-working smoke alarm. KNN_50 is the percentage of working smoke alarms in the 50 most similar homes. Floor area of the home shows in the top 10. Census/demographic data show in the top 30.

Figure 5 indicates the relative magnitude of feature importance and does not imply a positive or negative correlation. It should be noted that the chart isolates a feature in the correlation whereas in the model the features will have a lot of interactions with other features. The other point to note is that the correlation is based on a linear relationship when there is a more likely a curvilinear relationship. The correlations do not mean that there is a casual relationship between the feature and the prediction; however, these correlations do create a case for an argument that the feature and prediction are casually related, but more research would be needed.

Figure 10 Hamilton smoke alarm model feature importance




## Model Validation Metrics

As previous discussed, the "risk score" is built by uniformly binning the data on the output probability of the logistic regression for binary classification. As such, we are concerned more with overall performance as opposed to the ability to predict the correct probability, given that a relative probability amongst buildings is sufficient to construct the ranking. Accordingly, we follow the XGBoost [17] recommendation for modelling on an imbalanced dataset with a binary logistic objective, and with a focus on overall performance[1]. Specifically, we employ XGBoost's built-in *scale_pos_weight* parameter to balance the positive and negative weights in the training set and use Area Under Curve (AUC) as an evaluation metric. The *scale_pos_weight* is derived from the training set as follows:

$$\sum \text{negative instances} / \sum \text{positive instances}$$

For an evaluation of the model performance the following metrics are calculated:

- **Kappa statistic**

[1] Notes on Parameter Tuning, Handle Imbalanced Dataset, https://xgboost.readthedocs.io/en/latest/tutorials/param_tuning.html

- **Recall**
- **Precision**
- **AUC**

These values are shown in table 2 and compared against models in other cities. The other municipal models are targeting fire incidents in inspectable properties; however, the method and approach is very similar. Prediction models have a threshold where we need to find a balance between prioritizing inspections of buildings at higher risk probability and de-prioritizing buildings with less risk probability. This is the balance of finding the risky and non-risky buildings. Precision and recall inform on this balance. Precision is the fraction of actual events among the set of buildings predicted to have an event. If we classify all buildings as high risk, then we will find all the risky buildings, but we will also have included the non-risky buildings. In this case our success in finding high risk buildings would be perfect because we would be inspecting all the buildings in a community. However, this would not help prioritize inspections to buildings that are more likely to have an event (the event being either a fire or a non-working smoke alarm). A lower value for precision implies over classification of buildings as high risk (which may be intended so as not to miss some high-risk buildings). Table 2 shows that the New Westminster model achieves a recall of 0.41 at a precision of 0.47, whereas the Atlanta model achieves a recall of 0.72 with a precision of 0.18. More inspections are needed in Atlanta to find the buildings than in New Westminster. Precision in the Hamilton model is 0.42.

Table 2 Performance Metrics Summary

| Municipality | Kappa | Recall | Precision | AUC |
|---|---|---|---|---|
| **Hamilton Smoke Alarm** | 0.28 | 0.45 | 0.42 | 0.71 |
| **North Vancouver (District)** | 0.23 | 0.32 | 0.2 | 0.8 |
| **Richmond** | 0.25 | 0.5 | 0.19 | 0.91 |
| **Langley (Twp.)** | 0.32 | 0.33 | 0.36 | 0.82 |
| **Vancouver** | 0.3 | 0.35 | 0.34 | 0.78 |
| **New Westminster** | 0.42 | 0.41 | 0.47 | 0.83 |
| **Pittsburgh** | 0.33 | 0.5 | 0.26 | 0.75 |
| **Atlanta** | 0.17 | 0.72 | 0.18 | 0.8 |

Recall is the fraction of relevant buildings predicted to have a fire over the total number of relevant buildings. In other words, how many buildings that had an incident were classified as high risk. If we classify all buildings as high risk, then we will find 100% of risky buildings and the recall becomes 1. In table 2 Atlanta has a high recall of 0.72 i.e., for all the buildings that had fires in Atlanta the model had classified 72% as high risk. When this value is considered on its own the model appears to perform well but we need to also look at the precision to better understand the model.

The Kappa statistic measures the consistency between actual and predicted values, taking into account the agreement occurring by chance. Hamilton, the DNV, Richmond, Langley, Vancouver and New Westminster results in table 2; precision and recall values are measured at the probability threshold that maximizes Kappa.

It is important to note that sometimes over-classification is preferred as in the case of Pittsburgh. Pittsburgh has a higher recall but a lower precision. Pittsburgh Bureau of Fire (PBF) preferred to over-classify buildings as high risk. PBF prefers to inspect more buildings rather than have an issue with false negatives (properties classified as not risky that are high risk). As the model produces scores for all buildings it allows municipalities to choose their own threshold for targeting with prevention inspectors versus, for example, fire crews.

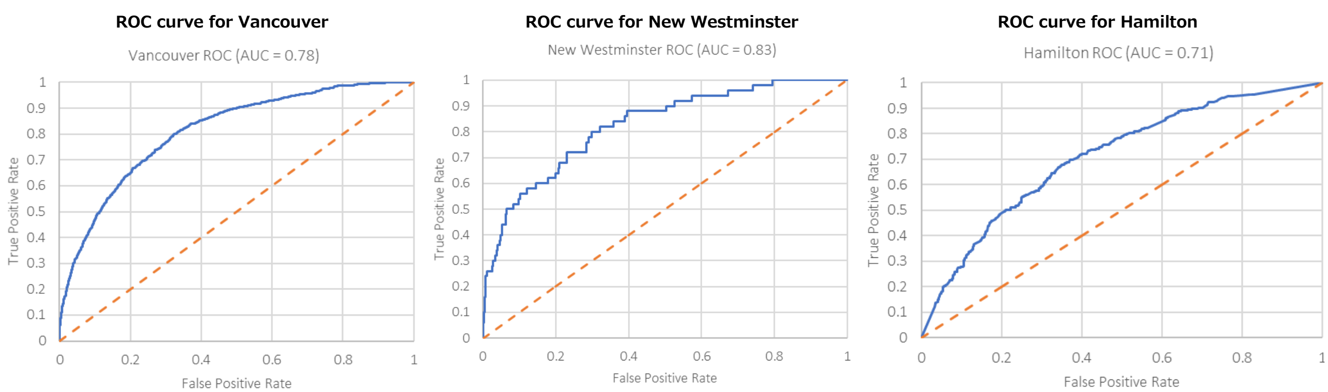
Model performance for a balanced dataset can be summarized by the ROC curve; however, the ROC is not a useful metric in imbalanced datasets. As these values were reported by New York, Atlanta, and Pittsburgh they are also presented here but provide limited information without precision. Due to class imbalance in fire incident data other metrics are also presented in this section. The following are used for ROC curves:

- **True Positive Rate (TPR)** – the ratio of correctly identified fire incidents divided by the total of all fire incidents

- **False Positive Rate (FPR)** – the ratio of falsely predicted fires divided by the total of all non-fire incidents
- **Area Under Curve (AUC)** – the area under the ROC curve (Receiver Operating Characteristic) where the ROC curve is a plot of the TPR vs. FPR.

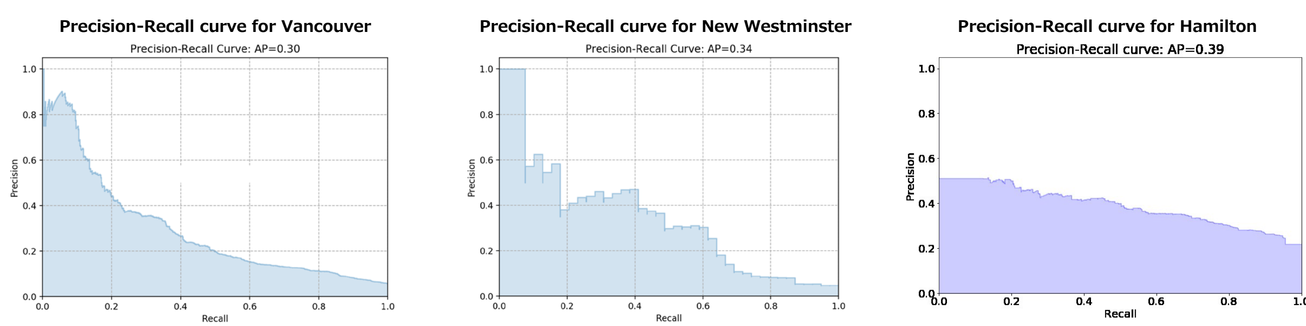
Figure 11 shows that at a true positive rate of 70% we see false positive rates of between 35-40% in the Hamilton model.

Figure 11 ROC curves




A Precision-Recall curve (PR-curve) is another effective way of evaluating model performance especially in the context of the business use-case. This will give us insight into how many buildings we might need to inspect to achieve the desired coverage of relevant buildings. Figure 12 shows the PR-curves for Vancouver and New Westminster. In Vancouver's case, precision drops relatively smoothly from a value of 0.8 beyond a recall of 0.1. At a recall of 0.5, precision crosses below 0.2. Comparatively, New Westminster's PR-curve has a more dynamic profile. Precision hovers around 0.45 between recall of 0.2 and 0.4, drops to an average of 0.35 between recall of 0.4 and 0.6, and drops again for recall greater than 0.65. Vancouver, New Westminster, and Hamilton have average precision values of 0.3, 0.34, and 0.39, respectively.

Figure 12 Precision-Recall curves




# Implications and Conclusion

## Current Performance vs. Targeted Performance

Figure 13 shows a summary of all the home inspections to verify working smoke alarms. Records where "no one home" are removed. The model prediction bins are also shown. HFD completed the highest number of inspections (2,308) in the lowest risk bin and found 91 homes in this risk category without a working smoke alarm, i.e., 4% of home visits found a non-working smoke alarm.

HFD completed 1,438 inspections in the highest risk bin (10) and found 408 non-working smoke alarms, i.e., 28% of visits found a non-working smoke alarm. Targeting properties in the highest risk bins (9/10) would be expected to find more properties without working smoke alarms. Ensuring more working smoke alarms in more homes should reduce the frequency and severity of residential fires based on the literature reviewed in this report.

An overview of the model prediction scores is shown in figure 14. Properties in risk bins 9 and 10 are coloured red.

Figure 13 2017-2019 home fire safety visit compared to model risk bins

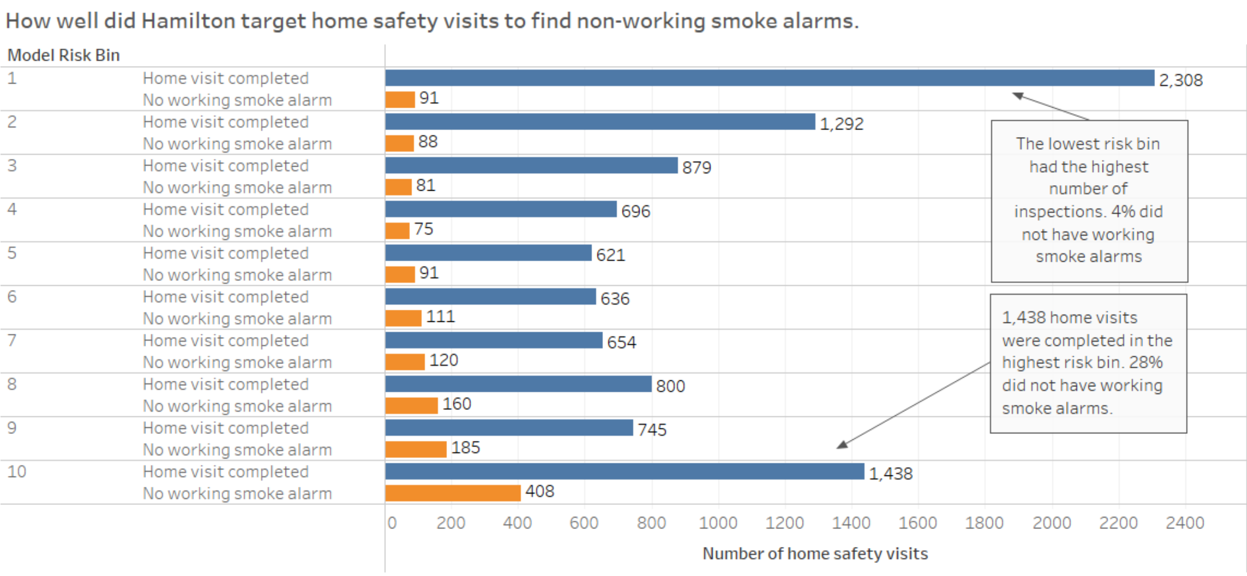
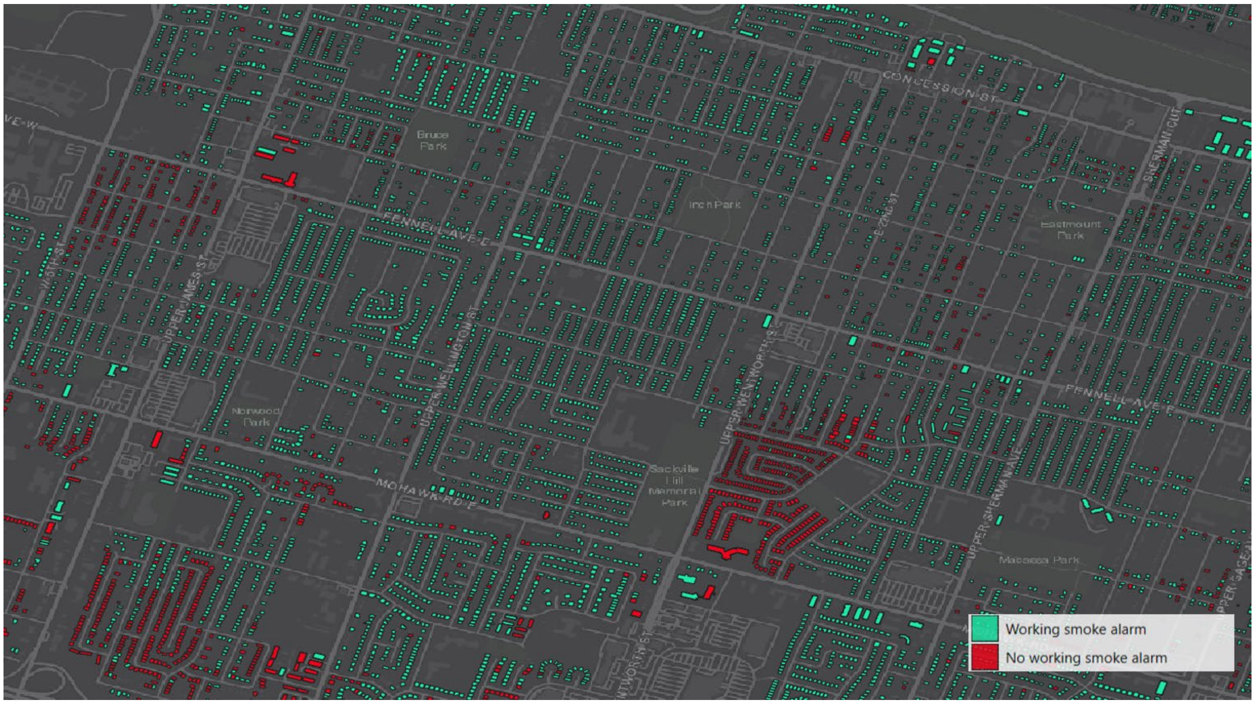



Figure 14 Hamilton model scores



## Conclusion

This proof-of-concept looked at how a machine learning approach to targeting home fire safety inspections could help to find properties with non-working smoke alarms. The model worked out the relative likelihood of not having a working smoke alarm and when tested on a dataset we see that 42% of the non-working smoke alarms are in the highest risk bins/scores. Based on the model results properties in higher risk bins should be prioritized for inspection if HFD aims to find more non-working smoke alarms.

Overall the concept of a community risk assessment is based on a risk matrix (see figure 15) as discussed in *NFPA 1300 – Standard on Community Risk Assessment and Community Risk Reduction Plan Development – A.5.6(4):*

> *"A risk assessment matrix classifies a community's risks based on **probability** and **impact**. This matrix is a tool that can be used to create a visual representation of the risks in the community. Figure A.5.6(4) is an example of a risk assessment matrix.*

Figure 15 Risk Assessment Matrix

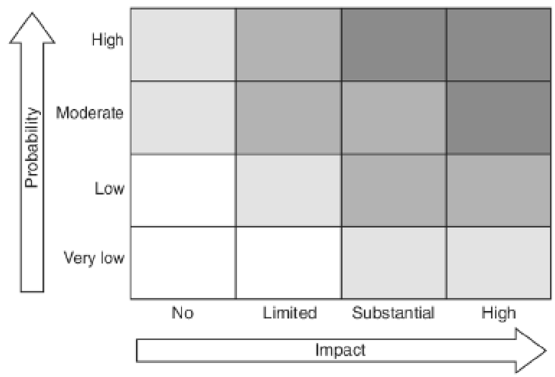



**FIGURE A.5.6(4) Risk Assessment Matrix.**

It is best to consider **impact** and **probability** together. For example, a residential apartment building may have more impact than a single-family home and therefore may need to be prioritized.

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