Identifying Locations for Public Access Defibrillators Using Mathematical Optimization

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Background—Geospatial methods using mathematical optimization to identify clusters of cardiac arrests and prioritize public locations for defibrillator deployment have not been studied. Our objective was to develop such a method and test its performance against a population-guided approach.

Methods and Results—All public location cardiac arrests in Toronto, Ontario, Canada, from December 16, 2005, to July 15, 2010, and all automated external defibrillator (AED) locations registered with Toronto Emergency Medical Services as of September 2009 were plotted geographically. Current AED coverage was quantified by determining the number of cardiac arrests occurring within 100 m of a registered AED. Clusters of cardiac arrests without a registered AED within 100 m were identified. With the use of mathematical optimization techniques, cardiac arrest coverage improvements were computed and shown to be superior to results from a population-guided deployment method. There were 1310 eligible public location cardiac arrests and 1669 registered AEDs. Of the eligible cardiac arrests, 304 were within 100 m of at least 1 registered AED (23% coverage). The average distance from a cardiac arrest to the closest AED was 281 m. With AEDs deployed in the top 30 locations, an additional 112 historical cardiac arrests would be covered (32% total coverage), and the average distance to the closest AED would be 262 m.

Conclusions—Geographic clusters of cardiac arrests can be easily identified and prioritized with the use of mathematical modeling. Optimized AED deployment can increase cardiac arrest coverage and decrease the distance to the closest AED. Mathematical modeling can augment public AED deployment programs. (***Circulation.*** **2013;127:1801-1809.**)

Key Words: automated external defibrillator ■ cardiac arrest ■ cardiopulmonary resuscitation ■ defibrillation ■ resuscitation

Out-of-hospital cardiac arrest (OHCA) is a significant public health problem, killing an estimated 300 000 people in North America annually.[1] The probability of survival after cardiac arrest decreases up to 10% with each minute of delay between collapse and treatment.[2,3] Only 5% to 10% of patients who suffer OHCA survive to hospital discharge.[1,4] Cardiopulmonary resuscitation (CPR) including quality chest compressions and early defibrillation can improve chances of survival for victims of OHCA. Patients suffering a witnessed cardiac arrest with a shockable rhythm who receive prompt CPR and defibrillation have markedly improved survival rates.[5–7] Public access defibrillation programs that deploy automated external defibrillators (AEDs) in public settings are feasible and have been associated with a doubling in survival from OHCA.[8–10] However, in the real world setting, AEDs are used before the arrival of emergency medical services (EMS) in <3% of OHCAs.[4] Effective use of an AED in the event of a cardiac arrest emergency requires that (1) an AED is in close proximity to the location of the cardiac arrest, (2) lay responders are aware of the location of the AED, and (3) lay responders are willing and able to retrieve and use the AED on the cardiac arrest victim. This investigation focuses on optimizing the first requirement.

Clinical Perspective on p 1809

Current guidelines suggest that areas associated with the highest risk of cardiac arrest should be targeted for AED deployment.[8] However, the method of identifying these cardiac arrest "hot spots" to optimize AED deployment in any given community is not clear. Throughout this article, we will refer to a cardiac arrest hot spot as a location with the occurrence of ≥1 historical cardiac arrests (over the 4.5-year time interval of the project) with no registered AED within a 100-m radius.

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Several studies have attempted to identify high-risk locations and building types for cardiac arrest.[11–17] These approaches have consistently identified facilities such as transportation hubs and large athletic venues as high risk, in which case it is thought that high population density drives the incidence of cardiac arrest upward. However, once the obvious choices for AED placement are identified and addressed, the challenge becomes one of deploying AEDs throughout the rest of the city in an efficient manner that maximizes coverage. For example, for a building-type category that has a high incidence of cardiac arrest but whose many constituent facilities are geographically dispersed, it may be prohibitively expensive to place an AED in each building in that category.[18] On the other hand, buildings in close geographic proximity may each belong to building categories with low cardiac arrest incidence but as a group may have above average cardiac arrest incidence. A pure building-type strategy would miss such a geographic hot spot. Furthermore, many cardiac arrests occur outside in a public area or on the street; building-type analyses are typically unable to differentiate between different outdoor areas. Finally, the generalizability of AED deployment strategies based on building-type information may be limited because of the heterogeneity of population demographics, local culture, and infrastructure from city to city.

In this article, we present a mathematical optimization methodology based on a well-established and previously validated optimization model for facility location[19] to identify geographic hot spots of cardiac arrest and prioritize them for public access defibrillator deployment. We also develop a population-guided AED deployment method for comparison. We present our results specific to the City of Toronto as an example of our methodology, which could be applied to other cities with available historical cardiac arrest data. The specific objectives of this study are (1) to quantify the level of coverage of historical cardiac arrests provided by registered public access defibrillators in Toronto, (2) to compare optimization and population-guided AED deployment methods, (3) to identify underserved cardiac arrest hot spots that may be target areas for future AED deployment, and (4) to quantify the improvement potential through geographic optimization of AED locations with the use of our optimization model.

Methods

Study Setting

Toronto has a population of ≈2.5 million, has a population density of 3972.4 people per square kilometer, and covers 630.18 km^2 of land.[20] The city is served primarily by a single EMS, but units from other bordering EMS services may respond to emergencies if they are closer. There is a tiered response to emergency calls, with the fire department and multiple EMS units often deployed to a single emergency call.

Study Design

We conducted a retrospective observational study of consecutive EMS-attended cardiac arrest episodes occurring within the boundaries of the City of Toronto, Ontario, Canada.

Cardiac Arrest Episode Selection

We considered all atraumatic cardiac arrest episodes occurring within the City of Toronto from December 16, 2005, to July 15, 2010, for inclusion in our study. We identified eligible episodes by the episode location postal code. Street address or latitude/longitude was used when a postal code was unavailable. Atraumatic cardiac arrest episodes were included regardless of initial cardiac arrest rhythm or presumed cause. We excluded those episodes that occurred in residential, nursing home, or healthcare facility settings or where it was not possible to determine with certainty the exact location of the cardiac arrest.

Data Sources

Cardiac Arrest Data

The Resuscitation Outcomes Consortium is a North American consortium of 11 coordinating centers and >200 EMS to enable multicenter randomized controlled trials in cardiac arrest and life-threatening trauma. The Resuscitation Outcomes Consortium Epistry–Cardiac Arrest database is a large registry of consecutive OHCAs attended by Resuscitation Outcomes Consortium EMS providers.[21] For this study, we used cardiac arrest cases from the local Epistry database occurring in the City of Toronto. Each entry in the database includes geographic information regarding the location of the cardiac arrest derived from dispatch data and the pickup location indicated by paramedics on the ambulance call report. A specific field in the database identifies whether or not a cardiac arrest occurred in a public setting. Patient demographics and clinical information regarding the characteristics of the cardiac arrest and treatment provided are also recorded for each episode. Approval for this study was obtained from our institutional research ethics board.

Locations of Registered AEDs

We obtained a list of 1669 registered AEDs in Toronto as of September 2009 from Toronto EMS. Toronto EMS dispatch sought to register all AEDs placed by several regional public access defibrillation programs and also advertised on its Web site for private owners of AEDs in the public setting to register their AEDs. The registration of public location AEDs is voluntary in Ontario. AEDs are registered in this database with the exact mailing address of the building in which it was placed and a contact telephone number. These data are integrated into a computer-assisted dispatch system used by the 911 operator.

Potential Locations for New AEDs

We used data from the 2009 City of Toronto Employment Survey (http://www.toronto.ca/demographics/surveys.htm, accessed August 22, 2011) obtained from the City Planning Division of the City of Toronto to determine potential locations for AEDs. This annual survey seeks to identify every business establishment in the City of Toronto. Data from the survey are gathered each summer by trained surveyors who canvas the entire city in person and conduct face-to-face structured interviews with representatives from >75 000 business establishments. In 2009, these businesses resided in 25 851 unique buildings in the City of Toronto. The survey collects location data on each of the buildings in which a surveyed business resides, including the number of floors within the building and number of businesses in each building. We used the geographic data corresponding to the unique buildings in this database to determine potential sites for public location AEDs.

Daytime Census Population

The City Planning Division of the City of Toronto used data from the 2006 Canadian Census to provide us with an estimate of the daytime population within each census tract. The daytime population for each census tract was calculated as the census tract resident population minus the used labor force (number of people in the census tract who are used) plus the place of work population (number of people who work in the census tract).[22]

Analyses

Geographic Data Conversion

Geographic data for all registered AEDs (in the form of street addresses), buildings in the City of Toronto (latitude/longitude

coordinates), and historical cardiac arrest cases (mix of addresses and latitudes/longitudes) were converted into the Universal Transverse Mercator format. The Universal Transverse Mercator system is similar to the well-known latitude/longitude system in its ability to uniquely identify a point on the earth's surface. One of the advantages of the Universal Transverse Mercator system is that it is based in meters rather than degrees and minutes, facilitating the calculation of distances. Once the data were converted into Universal Transverse Mercator coordinates, we plotted all data points in ArcGIS (Esri, Redlands, CA), a geographic information system software program. The distance from each cardiac arrest location to each current and potential AED location was calculated with the use of the Euclidean (ie, straight line) metric.

Analysis 1: Current Cardiac Arrest Coverage Level

Once all of the pairwise cardiac arrest–AED distances were calculated, we determined how many historical cardiac arrests occurred within 100 m of a registered AED. The 100-m coverage radius was chosen on the basis of the approximate maximum distance an AED could be transported by a bystander in a 1.5-minute walk as outlined in an American Heart Association recommendation for community AED placement.[8] This analysis addresses the first objective of quantifying the level of cardiac arrest coverage provided by currently registered AEDs.

Analysis 2: Comparing Optimization and Population-Guided AED Placement Strategies

To address the second objective of this article, we developed an optimization model based on the Maximal Covering Location Problem.[19] Details are provided in the online-only Data Supplement. Our model sought to identify a set of locations where placing AEDs would maximize the number of additional historical cardiac arrests that could be covered within a 100-m radius, above and beyond the number covered by existing registered AEDs. In our model, we assumed that existing registered AEDs could not be moved. The decision variables were the locations of the additional AEDs to be deployed, to be chosen from our database of buildings in Toronto. The model had 1 adjustable parameter, N, that specified the maximum number of locations where additional AEDs could be deployed. Solving the optimization problem with the parameter N set to 10, for example, would result in the identification of the top 10 cardiac arrest locations where additional AEDs would cover the most cardiac arrests. We ran the optimization model for values of N of 20, 40, 60, 80, and 100. A separate optimization problem was solved for each value of N. We used the AMPL (AMPL Optimization LLC, Albuquerque, NM) software language to code the algebraic formulation of the model, and we used the CPLEX (IBM Corp, Armonk, NY) solver to solve the corresponding optimization problem. The problems each took <15 seconds to solve with the use of a desktop computer with 6 GB of RAM and a quad-core 2.67-GHz processor.

We developed a population-guided AED placement method as an alternative for comparison with the optimization method. A population-guided model was thought to reflect a "common sense" deployment approach that is less complex and could be conducted without historical cardiac arrest data or an optimization model. We distributed the daytime population in each census tract among the buildings (from the Toronto Employment Survey database) situated in that census tract, proportional to the number of floors in each building. For each building, we took the fraction of the number of floors it had relative to the total number of floors in all buildings in the census tract and assigned that fraction of the daytime population in the census tract to that building. Then all buildings in Toronto were rank ordered on the basis of the assigned population, and the top N values were chosen as locations for AED placement. The values of N chosen were 20, 40, 60, 80, and 100. We also conducted a sensitivity analysis of the aforementioned approach by implementing a variant with the use of the number of businesses in each building, instead of the number of floors, to proportionally distribute population in each census tract.

To test the optimization method versus the population method, we applied the McNemar test for paired proportions.[23] We used 10-fold cross-validation,[24,25] in which in each scenario, 90% of the cardiac arrests (ie, the training set) were used by the optimization model to determine the N optimal AED locations, which were then used to measure the coverage provided to the remaining 10% of cardiac arrests (ie, the testing set). The testing sets were disjointed across the 10 scenarios. We solved the optimization model for each value of N 10 times, 1 for each scenario, and summed the coverage results over all testing data sets. We evaluated the population-guided method on the same 10 testing sets. The combined results were used to construct a 2-by-2 matched-pairs table for each value of N, where the diagonals counted the concordant pairs (the number of cardiac arrests covered by both optimization and population methods and the number covered by neither), and the off-diagonals counted the discordant pairs (the number covered by only 1 of the 2 methods). The McNemar test was performed on the 2-by-2 table for each value of N, and an associated P value was calculated. In addition, 95% confidence intervals for paired proportions, centered at zero, were constructed for all values of N.

Analysis 3: Optimization of AED Placement

To address the third and fourth objectives, we applied the optimization model to the full cardiac arrest data set for each value of N from 0 to the maximum number needed to cover all historical cardiac arrests.

Results

During this time period, there were 15 786 atraumatic cardiac arrests recorded in the greater Toronto area. After applying the exclusion criteria, there were 1310 public location cardiac arrests that occurred within the City of Toronto during the time period considered (Figure 1). Examples of public locations were outdoor settings, schools, public transportation venues, and commercial establishments. Demographics and cardiac arrest episode characteristics for the included cardiac arrests can be seen in Table 1.

Analysis 1: Current Cardiac Arrest Coverage Level

Of the 1310 public cardiac arrests considered, 304 of them occurred within 100 m of one of the 1669 preexisting registered public AEDs, which corresponds to a coverage percentage of 23% (304/1310). The average distance from a historical cardiac arrest to the closest AED was 281 m. We also conducted a post hoc analysis of the data stratified by whether the cardiac arrests occurred downtown or not, motivated by the observation that cardiac arrest density appeared to be significantly different between the areas when visualized with ArcGIS. Downtown was defined as the collection of census tracts that matched the downtown area defined by the City of Toronto[26] and covers 16.45 km^2 of land. There were 266 cardiac arrests that occurred downtown and 1044 cardiac arrests that occurred outside of downtown. The study data spanned 1688 days, and with the assumption of 365 days per year, the downtown cardiac arrest density was 3.5 cardiac arrests per square kilometer per year. Outside of downtown, the cardiac arrest density was 0.4 cardiac arrests per square kilometer per year. The results summarized in Table 2 show that the percentage of cardiac arrests covered in downtown was almost 3 times higher than outside of downtown and that the mean distance to the closest AED in downtown was ≈60% lower. The population of Toronto was 2 503 281 in 2006, which translates to 11.3 public location cardiac arrests per 100 000 people per year.

Figure 2 overlays historical cardiac arrests and existing AEDs on a map of the City of Toronto. The shaded pink

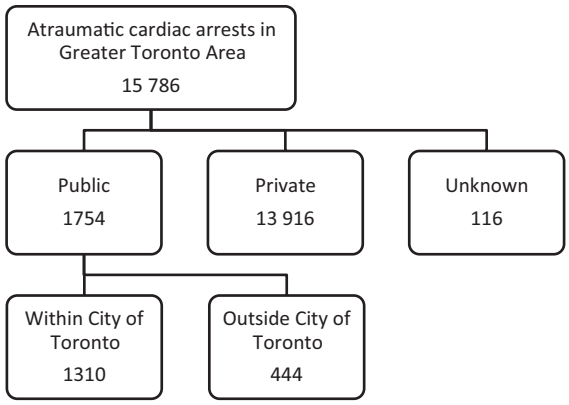

Figure 1. Criteria for cardiac arrest episode inclusion/exclusion.

region corresponds to downtown. Although there are many registered AEDs spread throughout Toronto, the vast majority have not historically been located within 100 m of a cardiac arrest. Figure 3 highlights the downtown area.

Analysis 2: Comparing Optimization and Population-Guided AED Placement Strategies

After the 304 cardiac arrests that were covered by the existing AEDs were removed, 1006 remained. Each of the 10 scenarios comprised a testing set with 100 cardiac arrests and a training set with the remaining 906. Table 3 displays the 2-by-2 table with the paired proportions for the case N=100. Similar tables were constructed for the other values of N. A P value <0.0001 (χ^2 statistic was 32.93 on 1 degree of freedom) was obtained from the McNemar test for N=100.

Figure 4 compares the coverage provided by the optimization method with the population-guided method. The midpoint of a confidence interval indicates the number of additional cardiac arrests covered with the use of the optimization method compared with the population method. The error bars represent 95% confidence intervals around the midpoint. Because we are using a paired difference in proportion centered at zero, the confidence intervals indicate statistical significance at the 95% level (P values were all <0.0001).

The sensitivity analysis showed that using the number of businesses in each building to proportionally distribute the daytime population in each census tract, instead of the number of floors, produced almost identical results. In particular, the optimization method covered more cardiac arrests than the business-based population-guided method across all levels of N.

Table 1. Demographic Characteristics of Included Public Location Cardiac Arrests

Characteristic	All Included Cardiac Arrests (n=1310)
Average age (±SD), y	59.4±17.6
Male	59.1±17.0
Female	60.8±19.9
Male sex, n (%)*	1052 (80.3)
Witnessed by bystander, n (%)*	582 (44.4)
Received bystander CPR, n (%)*	499 (38.1)
Received bystander AED, n (%)*	70 (5.3)
Average interval between 911 call and EMS vehicle arrival, min, median (IQR)*	5.7 (2.4)
Initial heart rhythm, n (%)*†	
Shockable	421 (32.1)
Not shockable	843 (64.4)
Survival to discharge*	160 (12.2)

AED indicates automated external defibrillator; CPR, cardiopulmonary resuscitation; EMS, emergency medical services; and IQR, interquartile range.

*Number of missing/not noted cases: male sex (17), witnessed by bystander (13), received bystander CPR (32), received bystander AED (76), average interval between 911 call and EMS vehicle arrival (21), initial heart rhythm (46), survival to discharge (4).

†Shockable includes ventricular tachycardia, ventricular fibrillation, and patients listed as shockable. Not shockable includes pulseless electrical activity, asystole, patients listed as not shockable, and patients in whom the initial rhythm was not obtained because resuscitation was stopped before rhythm analysis.

Analysis 3: Optimization of AED Placement

Figure 5 shows the results from running the optimization model on the full set of cardiac arrest data, varying the maximum number of locations for additional AED deployment. For example, placing AEDs in the top 30 locations resulted in coverage of an additional 112 historical cardiac arrests, corresponding to an overall coverage percentage of 32% (416/1310; a 9% improvement over the baseline calculated in analysis 1). In this case, the average distance from a cardiac arrest to the closest AED decreased to 262 m. Reducing the distance a bystander needs to travel by ≈20 m, or up to 40 m round trip, has the potential to save close to half a minute in response time. Each cardiac arrest hot spot in the top 30 was composed of at least 3 cardiac arrests. After AEDs were placed in the top 111 locations, each subsequent AED placed covered 1 historical cardiac arrest.

Figure 6 illustrates an example output of the optimization, identifying the top 30 locations for additional AED deployment.

Discussion

Previous studies have indicated that strategic initiatives are needed to target high-incidence areas of cardiac arrest and that without a coordinated approach to AED deployment, paradoxical placement could result, with many AEDs placed in areas of low cardiac arrest incidence.[14] This study demonstrates that strategic placement of AEDs in a limited number of sites may result in an increase in cardiac arrest coverage in a large urban center. Such an increase will correspond to a decrease in the average distance from a cardiac arrest to the nearest AED and may ultimately result in faster response times and improved outcomes. According to both the European Resuscitation Council[27] and American Heart Association[8] recommendations for AED deployment (placing AEDs in areas with 1 cardiac arrest every 2 and 5 years, respectively), the top 30 cardiac arrest hot spots identified would be locations recommended for AED placement. The results shown in Table 2 highlight the epidemiological paradox of AED efficiency in dense, downtown settings versus more rural settings outside downtown. In particular, almost half of all downtown cardiac arrests were covered by

Table 2. Baseline Cardiac Arrest Coverage Provided By Existing Registered AEDs in Toronto

Area	Total No. of CAs	Total No. of AEDs	Total No. of CAs Covered	Coverage, %	Mean Distance to Closest AED, m*
Downtown	266	303	130	49	129±103
Outside downtown	1044	1366	174	17	319±237
Overall	1310	1669	304	23	281±229

AED indicates automated external defibrillator; and CA, cardiac arrest.
*Plus-minus values are mean±SD.

an existing AED, whereas only 17% of cardiac arrests outside downtown were covered. This drop in coverage contrasts sharply with the number of AEDs and cardiac arrests outside downtown, which is ≈4 times more than the number of AEDs and cardiac arrests inside downtown.

Our optimization model should be viewed as a decision-support tool to help prioritize placement of AEDs; make efficient use of public, donor, or private funds directed toward public access defibrillation programs; and potentially maximize survival on the basis of geographic patterns of cardiac arrest. Because AEDs are expensive and cannot be placed everywhere, our model allows a decision maker to quantify the trade-off between the number of AEDs deployed and coverage. Geographic optimization of AED placement should be seen as a complementary approach to existing AED deployment methods. After priority hot spots are identified through our optimization model, a detailed study of the buildings in the area should be conducted before a decision is made about specific locations to place AEDs. Data from other building-specific analyses may inform these "micro"-level decisions. For instance, an important consideration is the hours a building is open. The locations identified for potential AED deployment in this article tended to have many other buildings nearby, either next door or across the street. Therefore, given an optimal location identified by our model, it seems likely that there would be many candidate locations that would provide equal coverage, with at least 1 having regular business hours. The specific results of where to place the AEDs in the City of Toronto to optimize coverage of potential cardiac arrests are not meant to be generalizable to other cities; rather, it is the optimization methodology itself that we believe can be translated and used by other cities to generate customized recommendations using their region-specific data and preexisting AED deployment patterns.

Our model is based on a well-established, previously validated model used to solve the problem of optimally locating public facilities.[19] Since then, similar models have been developed to determine the deployment of preventative healthcare facilities[28–30] and blood banks,[31] as well as for EMS applications like ambulance location[32] and EMS station location problems.[33] As opposed to generating a simple ranked list of hot spots based on the number of uncovered cardiac arrests, the priority locations determined by the optimization model will change depending on the choice of the parameter N (the number of locations where AEDs may be deployed). Because each choice of N results in the solving of an independent optimization problem, our model is able to properly account for overlap between the radii of nearby AEDs and to account for cardiac arrests that are already covered by previously deployed AEDs.

Optimization models can also be used to test different hypotheses or policies regarding AED deployment. For example, the coverage provided by deploying AEDs in all gas stations in a region to treat cardiac arrests that occur on the street can be explored computationally. Potential partnerships with businesses such as coffee shops or restaurants to deploy AEDs in their retail facilities could be evaluated computationally in terms of coverage provided by their network of locations. Finally, a similar model could be used to "right-size" the number of public access defibrillators needed in a given region. Decision makers interested in achieving a particular service or coverage level (eg, 95% of historical cardiac arrests must be within a 100-m distance or a 2-minute travel time from a public access defibrillator) provided by public AEDs in their

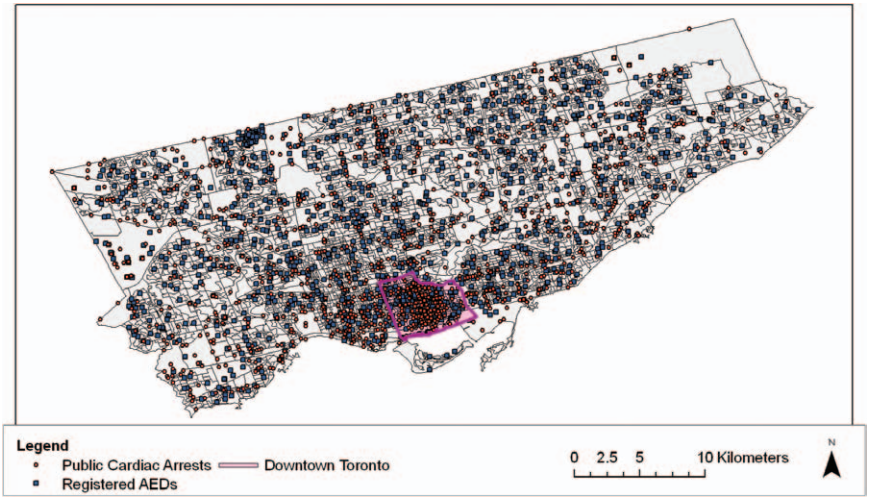

Figure 2. Geographic distribution of public location cardiac arrests from December 16, 2005, to July 15, 2010, and registered automated external defibrillators (AEDs) as of September 2009.

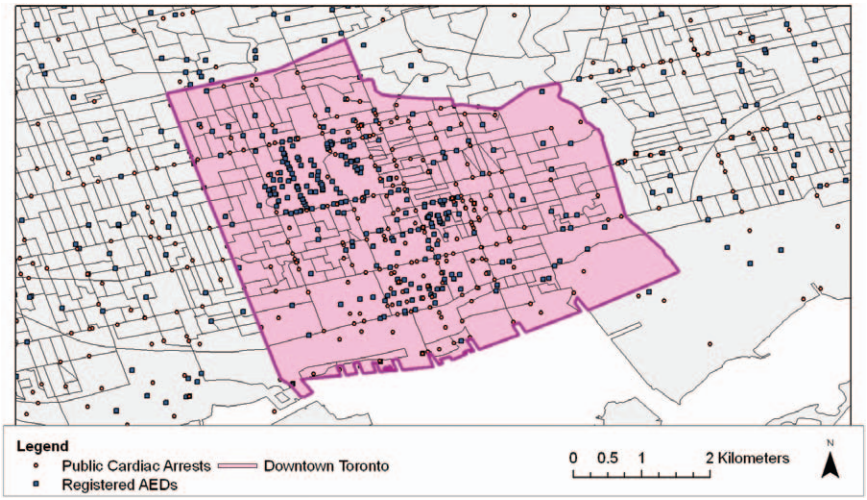

Figure 3. Public location cardiac arrests and registered automated external defibrillators (AEDs) in and around downtown Toronto.

region could leverage a mathematical model similar to the one used in this article to calculate the number and locations of the AEDs required.

Deploying public AEDs in accordance with population density is a very intuitive and appealing idea but is challenging to implement in practice. Population data are often captured only at the census tract level, which lacks the geographic granularity needed for public AED deployment decisions. Detailed building data similar to those we collected in this article may not be easy to obtain. Finally, obtaining daytime population data may be a challenge because census information is based on residential addresses. Given the challenges in obtaining granular daytime population data and the better performance of the optimization method over the population-guided methods demonstrated in this article, the effort to develop population cardiac arrest databases for use in optimization-guided health interventions may be justified.

The analyses in this article were conducted from a geospatial point of view. Physical obstacles like doors, walls, corners, and multiple floors were not explicitly modeled. Our analyses are meant to provide a high-level view of geographies or regions where there are higher densities of cardiac arrests that are underserved by existing registered AEDs and that therefore may be appropriate places to focus effort in placing future AEDs. By measuring coverage of historical cardiac arrests and identifying historical hot spots as potential geographies for future AED deployment, we implicitly assume that the past distribution of cardiac arrests is representative of the future. It has been shown in at least 1 city that the incidence of cardiac arrest within census tracts is relatively stable from year to year.[34] The cross-validation approach taken in this article is 1 method to account for variability in cardiac arrest locations.

The database of building locations from the City of Toronto was used as our "grid" on which to identify cardiac arrest hot spots, but not all of those buildings would be an appropriate location in which to place an AED; actual deployment will require on-site evaluation to consider architectural details and building function. Furthermore, many buildings will require multiple AEDs to service all of the potential need (eg, multistory buildings). However, this database provides a convenient mechanism to evaluate a diverse set of geographic points dispersed across the city and is generally aligned with the distribution of population density. Therefore, it is reasonable to assume that potential locations for new AEDs will be in close proximity to buildings in this database.

It is important to recognize that our concept of "coverage" and actual AED usage are completely separate issues. Our claim is not that an AED within 100 m will definitely be used. Rather, the coverage radius is used to quantify how many AEDs have a chance of being used. Our focus is purely on identifying geographic hot spots and determining

Table 3. Coverage of Cardiac Arrests According to Optimization (N=100) and Population-Guided Methods

	Population-Guided Method		
	No	Yes	Total
Optimization method			
No	882	26	908
Yes	87	5	92
Total	969	31	1000

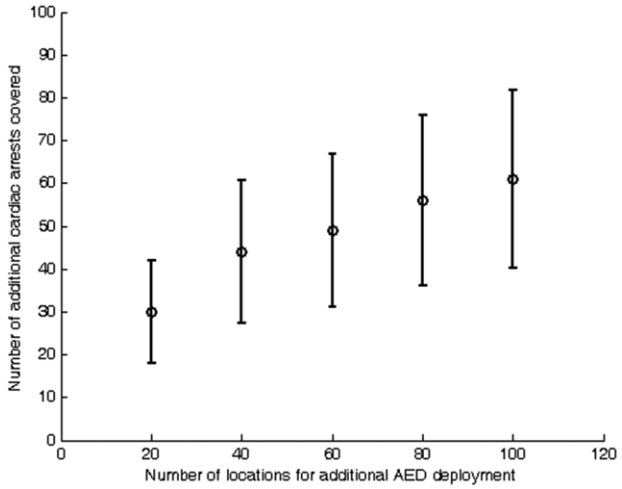

Figure 4. Number of additional cardiac arrests that the optimization method covers over the population-guided method. AED indicates automated external defibrillator.

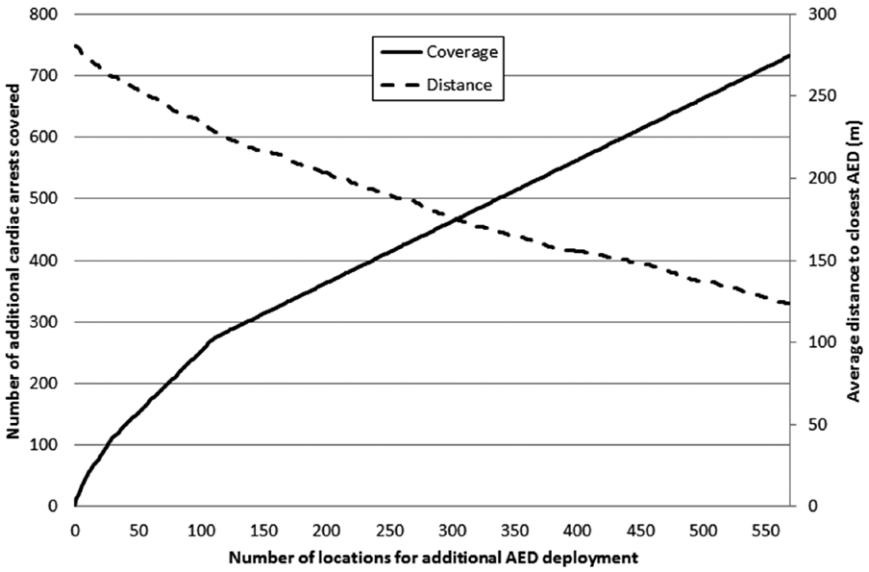

Figure 5. Increase in cardiac arrest coverage and decrease in average distance between cardiac arrests and the closest automated external defibrillator (AED) as a function of increasing AED deployment.

the existence of nearby AEDs; we make no claim on understanding actual bystander behavior and the resulting AED usage in cardiac arrest situations. Because of the relatively short distances bystanders are expected to travel to retrieve a nearby AED, we believe that the straight line metric provided a reasonable approximation to distance traveled on foot. Interventions that increase bystander recruitment to a cardiac emergency or bystander awareness of AED locations at the time of a cardiac arrest have the potential to increase the coverage radius of an AED. For example, trained bystanders could act as an extension of EMS if they are alerted through a cellular telephone of a nearby cardiac arrest and respond accordingly. Instead of round-trip travel by a bystander close to the victim, a targeted responder can make a 1-way trip with an AED, cutting the travel time in half or, equivalently, doubling the coverage radius.[35] A faster response time is associated with an increase in the likelihood of a shockable initial rhythm. Figure 5 shows that as more AEDs are added to the system, the incremental value of each addition decreases. These results highlight the need to both optimize AED deployment in a large urban center and integrate the AED network with EMS and lay responders.

Registration of AEDs is not mandatory in Ontario and many other jurisdictions around the world. The list of registered AEDs obtained from Toronto EMS may not capture all publicly accessible AEDs in Toronto. However, we believe that this is only a mild limitation. A 911 operator would not be able to direct a caller to an unregistered AED, and therefore the likelihood that it would be used in a cardiac arrest is probably low, even if it is nearby. Unregistered AEDs tend to be purchased corporately and remain under lock and key as part of the institutional response to an internal emergency. Thus, we believe that using our list of registered AEDs is a reasonably accurate way to determine coverage of cardiac arrest cases that are reported to 911. Another limitation of this data source is that it does not include the date that the AED was installed (or provide any guarantee that the AED is still present and functional). The result is that the calculations of cardiac arrest coverage will be overestimated. However, our focus has been on the change in coverage and change in distance to the closest AED relative to a baseline, which means that although absolute values will be overestimated, relative values should be fairly accurate. In any case, this data limitation reinforces the need to develop local and national registries of publicly

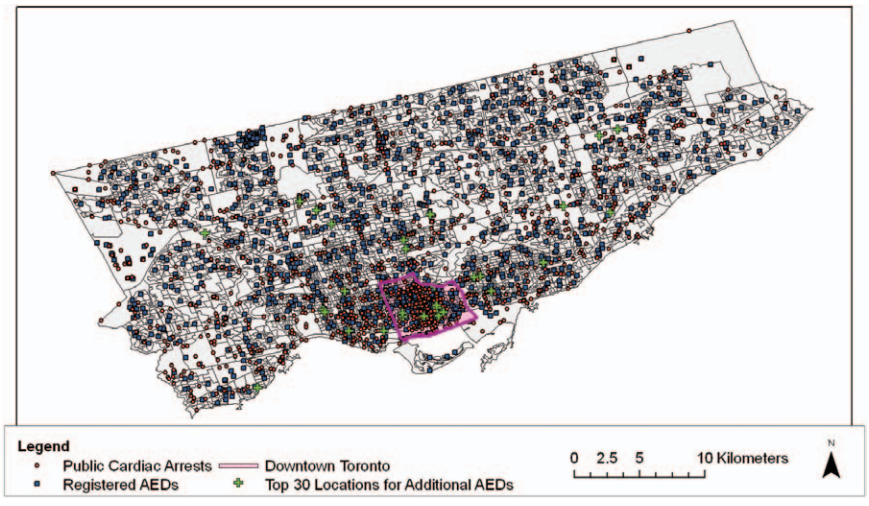

Figure 6. Locations of top 30 uncovered cardiac arrest hot spots in Toronto. AED indicates automated external defibrillator.

accessible AEDs and to involve public health organizations, EMS, and the public itself in helping to register AEDs.

Finally, defibrillation is only 1 component of the optimal bystander response to cardiac arrest. It may be argued that good-quality bystander CPR is a more important component of bystander resuscitation given that it is indicated for nearly all atraumatic cardiac arrest victims; an AED is effective for the minority of OHCA patients who have a shockable cardiac rhythm at any time. Any analysis that identifies cardiac arrest clusters should not only guide the rational placement of AEDs but also direct focused efforts to increase bystander CPR through awareness campaigns, training, or the establishment of organized first-responder programs.

Conclusions

A mathematical optimization model can be used to detect geographic hot spots of cardiac arrest and drive regionally customized strategic initiatives aimed at deploying public access defibrillators in areas of a city with the highest incidence of cardiac arrest. In particular, we demonstrate that an appropriate optimization model can outperform population-guided approaches to AED deployment. By targeting appropriate areas for AED deployment, coverage of potential cardiac arrest sites can be increased, and the distance a lay responder needs to travel to retrieve an AED can be decreased. Mathematical modeling and optimization methods should be a part of a comprehensive, data-driven approach to AED deployment in public access defibrillation programs.

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Disclosures

None.

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CLINICAL PERSPECTIVE

Hundreds of thousands of people suffer out-of-hospital cardiac arrest in North America every year. Early recognition and bystander resuscitative efforts are associated with improved chances of survival. For those with ventricular fibrillation or pulseless tachycardia, prompt defibrillation with an automated external defibrillator (AED) can allow return of spontaneous circulation and markedly reduce morbidity and mortality. Delaying defibrillation until the arrival of professional rescuers is associated with reduced probability of survival. Unfortunately, public access defibrillators are rarely used. Despite best efforts by governments, emergency medical services, charities, and citizens to place AEDs in optimal locations, this process is usually not driven by cardiac arrest location data. This article describes the use of historical cardiac arrest data in the city of Toronto and the application of a well-known and validated mathematical optimization model to guide AED placement. This strategy for planning AED distribution is compared with a “common sense” method based on daytime population estimates. The investigators in this study describe how the mathematical optimization strategy appears superior to the current population-guided strategy when evaluated with cross-validation and the metric of historical cardiac arrest coverage. The results of this article provide guidance for other communities seeking to optimize AED placement with a data-driven approach.

Identifying Locations for Public Access Defibrillators Using Mathematical Optimization

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Supplemental Material

Supplemental Methods

The mathematical model we use is shown below.

- x_j is a binary variable indicating whether cardiac arrest *j* is covered or not
- y_i is a binary variable indicating whether an AED is placed in location *i* or not
- a_{ij} is a binary data parameter that indicates whether cardiac arrest *j* is coverable (within 100 meters) of location *i*
- N is the number of locations in which AEDs are placed
- I is the number of potential locations in which to place AEDs
- J is the number of cardiac arrests in our dataset

$$\begin{aligned} \text{Maximize} \quad & \sum_{j=1}^{J} x_j \\ \text{Subject to} \quad & \sum_{i=1}^{I} y_i = N \\ & x_j \leq \sum_{i=1}^{I} a_{ij} y_i, \ \text{for all } j = 1, \dots, J \\ & x_j \in \{0,1\}, \ \text{for all } j = 1, \dots, J \\ & y_i \in \{0,1\}, \ \text{for all } i = 1, \dots, I \end{aligned}$$

This is a binary optimization model also known as the Maximal Covering Location Problem[1].

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