A Novel Framework for Automated External Defibrillator Deployment (FAEDD) in Identified High Risk Residential Areas

MSc Research Project
MSCDAD-A

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MSc Project Submission Sheet

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Title

Full Title: A Novel Framework for Automated External Defibrillator Deployment (FAEDD) in Identified High-Risk Residential Areas

Short Title: Framework for Automated External Defibrillator Deployment in Residential Areas

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Cover Letter

Dear J. Robinson,

We are submitting a manuscript for submission to PLOS ONE entitled "A Novel Framework for Automated External Defibrillator Deployment (FAEDD) in Identified High-Risk Residential Areas".

Residential areas have been under researched in terms of identification and deployment framework for AEDs to combat a cardiac arrest. A person is likely to survive a cardiac arrest in a public space when compared to a residential space, which is true for Ireland and at a global level, due to available resources. The optimal time for defibrillation is 3 minutes and if no intervention, every minute chances of survival decrease by 10% resulting in death by 10 minutes. This research is important to guide public resources to identify the most at-risk areas in need of an AED and a deployment framework to guide the optimal location of an AED in residential areas. Few studies have tried to create a framework to guide resources specifically targeting residential areas and tend to rely on historic OHCA data to guide deployment which is not always a future predictor.

In this paper, we analyse socio-economic behaviours of electoral divisions in Ireland, to determine the highest at-risk areas in terms of health using Bayesian Conditional Auto Regressive techniques. The findings are cross referenced with current resources of Community First Responder Groups and current AEDs within the area. This research then uses a proof-of-concept model to illustrate how a residential road network can be used as a proxy for determining optimal deployment of an AED based on distance using Maximal Coverage Location Problem. The framework illustrates an optimal guide for public resource deployment and encourages communication with residential areas on AED deployment to help increase survival rates by retrieving an AED within the optimal timeframe to mitigate death.

This paper expands on the work of Masterson et al (2018) and Tierney et al (2019) who used Bayesian methods to identify risk and the work of AED deployment by Metrot et al (2019) who use

MCLP for AED deployment. We certify that this paper consists of original, unpublished work which is not under consideration for publication elsewhere.

We hope you will consider this manuscript for publication and that it meets the high standards of your journal. We look forward to your response from you regarding our manuscript.

Best Regards.

Celine Moran Lee (corresponding author)

20th September 2021

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Title Page

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A Novel Framework for Automated External Defibrillator Deployment (FAEDD) in Identified High-Risk Residential Areas

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Abstract

An Automated External Defibrillator (AED) are portable devices deployed in high footfall areas that are used to resuscitate a person from Cardiac Arrest. The challenge is to identify high risk areas in need of an AED and the most optimal placement of an AED. Current research indicates this challenge is highest in residential areas which are at most risk of an Out of Hospital Cardiac Arrest (OHCA) however most public and private resources has implemented AEDs in high traffic public areas such as workplaces, train stations, airports, and shopping areas.

This research proposes a framework by applying various Bayesian CAR models using Poisson, Gaussian distributions to identify the most high-risk areas using variables related to health and material deprivation from the Irish census 2016. The AED deployment framework uses MCLP and programming to identify potential AED locations specifically targeting residential areas. The main findings from this research indicates that using various Bayesian models, when compared identifies an overlap in several areas classed as high-risk. In terms of AED deployment, the proposed MCLP model used within this paper accounts for the entire spatial area of 400 metres between potential AED locations in every direction to the boundary. This allowed for coverage of every hypothetical OHCA on every residential road.

The significance of this framework to public bodies and medical resource deployment services, is a robust, conclusive Bayesian CAR model to indicate highest risk areas and a scale for residential AED deployment based on distance and number of AEDs using MCLP. The key to application of this research is communication of resources available and if AEDs are deployed,

awareness of AED location and mode of transport for retrieval with the occupants of each residential unit to ensure a clear understanding of time and distance to retrieve.

Introduction

The survival rate of Out-of-hospital cardiac arrest (OHCA) is less than 10% globally (Ringh et al, 2018) which Ireland is aligned to (OHCAR, 2019). In Ireland approximately 54 of every 100,000 people will experience an OHCA with two thirds occurring in a residential area and one third in a public space (e.g. train station, shopping area). Residential OHCA have an 18% chance of survival when compared to OHCA in public places at 42% (OHCAR, 2019). The causes of OHCA vary from heart disease, trauma to the heart, asphyxiation and can often be a by-product of poor health factors (OHCAR, 2019). An OHCA can happen with little warning and every minute without intervention (CPR/AED/EMS) can result in a 10% decrease in survival (Weaver et al 1987; Perkins et al, 2015; Masterson et al, 2016) resulting in imminent death in 10 minutes (OHCAR, 2019). Use of an Automated External Defibrillator (AED) within a few minutes of collapse can result in an increase of survival by 50%-70% (Masterson et al, 2018; Ringh et al, 2018; Perkins et al, 2015; Olasveengen et al, 2021).

Currently, there is no national coordinated implementation strategy of AED deployment within residential areas in Ireland and there is no public optimization strategy to guide voluntary organisations on placement of AEDs in residential areas. Thus, a gap exists for a model that can determine high risk poor health areas in need of imminent AED deployment with a framework to guide the deployment of AEDs within a high-risk residential community.

The aim of this research is to investigate a suitable framework from public resources to identify poor areas of health and develop a suitable framework for the most optimal AED deployment in residential areas within the most at-risk areas. The research question is "Can publicly accessible data help define a framework that identifies high-risk health electoral divisions using Bayesian methods and using an optimisation method can the optimal coverage be determined within residential areas?". To address the research question, the following specific sets of research objectives were derived:

1. Investigate the state of the art in relation to AED deployment and identification of OHCA high risk areas using socio-economic factors.
2. Design a framework that will identify the most at-risk areas.
3. Design and implement a model for optimal placement of AEDs in residential areas using MCLP.
4. Evaluate the model using evaluation techniques.

This project will address each of the research objectives using data of current registered AED deployment within Ireland, the novel use of census 2016 socio-economic data, current registered AEDs from the EMS and the residential road network for Ireland.

The major contribution of this research is a novel approach to identify high-risk OHCA using the census 2016 socio-economic data; and a framework to identify optimisation deployment of AEDs in residential areas, a first attempt in academia in terms of an Irish context. This project is expected to benefit communities in need of greater resources; a reduction in cost related to lengthy and expensive treatment of OHCA due to lack of AEDs; and this research is expected to contribute to a HSE strategy of community OHCA resources and a reduction of costs to the HSE.

The structure of this paper discusses related further related work split between the proposed framework sections of 'OHCA Area Risk Identification' and 'AED Deployment Strategies' which discuss the statistics related to OHCA and Survival; strategies for identification of high-risk OHCA; and optimisation strategies for AED deployment. This is followed by a design overview of the framework and design specification for this project. This is the proceeded by the Results section where all results are presented together with a Discussion and Conclusion section discussing the key aspects of the results and implications for the framework.

OHCA Area Risk Identification

The identification of OHCA risk and where to deploy an AED is an unresolved definitive problem. Currently the recommendation by the AHA and the ERC is to place an AED in an area where an OHCA is likely to be witnessed, movement of people (Kronick et al, 2015) and/or in an area where an OHCA has occurred in the past 5 years (Perkins et al, 2015; Olasveengen et al, 2021). This approach has been used in various studies where historical OHCA registry has been used to identify area risk (Al-Drury et al, 2020; Auricchio et al, 2020; Lin et al, 2016; Sun et al, 2016; Sun, 2020; Tierney et al, 2019; Tsai et al, 2012). The challenge with using only historical data, is that there is no prediction for the rest of the population to a likelihood of an OHCA occurring. Demographic variables such as age, location and socio-economic variables have been identified from historical OHCA data (Al-Dury et al, 2020) as factors that can be used to identify population clusters of poor health (Masterson et al, 2018; Xia et al, 2020).

Lorenzo et al (2020) used a geographic risk function with data related to AED locations and OHCA historical data. The risk function also accounted for the total population of the city of Milan and not just the historical coverage. This method indicated that 40% of the overall population of Milan was covered with a suggested focus for future models to concentrate on residential deployment of AEDs to cover a wider population and reduce the risk of inaccessibility to an AED (Lorenzo et al, 2020).

Masterson et al (2018) used Bayesian Conditional Autoregressive (CAR) method with a Poisson assumption, fitted with MCMC and tested for spatial autocorrelation with Moran's I statistic. The variables within the Bayesian CAR method included historical data of OHCA between at home and not at home, which were compared against characteristics of the wider population with variables from the 2011 census. The selected variables from the census included a self-assessed health variable, age and Principal Component Analysis was applied to variables that indicate high material deprivation which have been linked to poorer health. Within the research it was found higher incidences of OHCA intervention in the form of CFR and AED bystander use increased with rurality and an OHCA was most likely to occur at home (Masterson et al, 2018).

A Bayesian CAR method was also used to determine spatial clusters of Tuberculosis (TB) in China. This method used historical data of TB cases and socio-economic variables related to employment, demographic characteristics, population density and health resources from public database sources. These variables were standardized and fitted with INLA using univariate and multivariate models. Spatial autocorrelation was tested using Moran's I index. The research found those of a lower socio-economic status and age increased the likelihood of spatial clusters for TB (Xia et al, 2020).

Bayesian CAR methods with spatial smoothing are indicated to be a useful tool to indicate likelihood of area risk as the spatial smoothing considers neighbouring regions to determine spatial clusters.

AED Deployment Strategies

AED residential deployment has been identified as an important area to increase survival rates (Folke et al, 2010; Lorenzo et al, 2020; Masterson et al, 2018; Rao et al, 2019; Ringh et al, 2018). It is recommended within a residential deployment strategy to consider AEDs linked to EMS; availability to an AED 24 hours a day 7 days a week; placement outside of the home, not in the home; the use of statistical models to determine the optimal location of AEDs for residential access; and that the AED has a protective case to prevent theft (Ringh et al, 2018). Thus, a gap exists where AEDs are generally not accessible on residential public roads nationally.

Within Ireland voluntary CFR groups have fulfilled the role of providing an AED within the community by bringing the AED to an OHCA location. This can take longer than 3-minutes, the optimal time for defibrillation (Ringh et al, 2018). As there is no national strategic guidance or an obligation to register the AED with the EMS, a gap exists where AEDs are generally not accessible on residential public roads nationally and an over reliance for a CFR member to bring an AED to an OHCA location.

The most common deployment strategy for AEDs is based on mathematical optimization models such as Maximal Coverage Location Problem (MCLP) to determine area coverage or Geographic Information Systems (GIS) to calculate walking route distance of an AED. The general guidance is to place an AED within high-footfall areas in public spaces. Within the domain, distances for AED placement have been analysed from 100 meters and 400 meters (Bonnet et al, 2015; Folke et al, 2010; Huang and Wen, 2014; Tsai et al, 2012) to a potential OHCA and/or a 3-minute round trip of retrieval (Ringh et al, 2018).

Spatial-temporal optimization strategies have been used for deployment of AEDs where placement is in a time sensitive location with limited access by time of day (Sun et al, 2017). The spatial distance is calculated within the area to previous OHCA, and the temporal coverage is based on time of day. This model is useful when AEDs are not placed on publicly accessible roads.

Sun et al (2020) used an optimization strategy to calculate AED deployment of 100-meter distance against a guideline approach which led to a reduced number of AEDs. This was based on historical OHCA data, however there was no accountability for residential coverage within the model.

Rao et al (2019) uses a multi-objective optimization strategy to deploy AEDs within a specific area using a walking route-based criteria for collection of AEDs to an OHCA location. This method was applied in an urban area with no allowance for residential access.

Tierney et al (2020) used a combination of Bayesian CAR fitted with INLA and a catchment area approach to determine coverage of AEDs and risk within Ticino in Switzerland. The deployment of AEDs was measured against the relative risk of the area and a comparison to current resources within the area. This approach accounted for the financial resources of the area but no allowance for residential deployment.

One of the most common methods to determine a framework coverage of a population (historical or total population) is the use of MCLP. Based on various criteria for coverage MCLP aims to achieve the maximal coverage of a particular area. This method was used by Bonnet et al (2014) to reposition AEDs with an interactive mapping tool and measuring success based on MCLP to determine the coverage. This method was also used by Metrot et al (2019) to determine the maximal coverage of the population based on random deployment of AEDs against hypothetical OHCA locations within Beirut city (Metrot et al, 2019).

The key findings from the literature indicate the focus of past research have been to explain historical OHCA and implications for AED deployment. There is a lack of focus on accessible methods to the public focusing on identifying high risk areas from public data and developing a framework to deploy AEDs. The aim of this research is to investigate a suitable framework from public resources to identify poor areas of health and develop a suitable framework for the most optimal AED deployment in residential areas within the most at-risk areas. The research question is “Can publicly accessible data help define a framework that identifies high-risk health electoral divisions using Bayesian methods and using an optimisation method can the optimal coverage be determined within residential areas?”.

The current identified gap within the domain is a deployment framework for residential areas and identification of high-risk areas using the methods of Bayesian CAR and Moran’s I statistic methods to identify spatial clusters is the most optimal method to identify high-risk areas in Ireland. Of those high-risk areas, MCLP is a good framework to determine AED deployment within residential communities provided each residential unit are aware of the distance to the nearest AED and mode of transport for retrieval.

Materials and Methods

For illustration of this framework, data related to the Republic of Ireland will be used as proof of concept of framework. The 2016 census of the Republic of Ireland indicates a total population of 4.7million spread across a total of 3,409 Electoral Divisions (EDs) and 70,273 square kilometres. There are 28 counties in the Republic of Ireland, with a quarter of the population residing within Dublin city and county, with the rest of the population spread across the other 27 counties in cities, towns, villages, and rural areas.

The EMS team in Ireland is the sole provider of emergency response care to respond to OHCA with the Irish National Ambulance Service responding across all areas except for Dublin where there is an added resource of the Dublin Fire Brigade. When a call related to an OHCA is placed to the EMS team, the dispatcher deploys the relevant emergency response vehicle and checks the database to determine if there is a local CFR group and/or publicly accessible AED registered with the EMS (OHCAR, 2019).

Data

The National Ambulance Service (NAS) shared data related to AEDs registered with the EMS team as of January 2021 which was approved by the Irish Health Executive Board (HSE). A total of 2,143 registered AEDs that were geo coded to a total of 1,372 CSO Small Area. This data was then transferred from CSO Small Area to Electoral Division. The automated external defibrillator (AED) location data used by NAS is provided by the owners of the AED and that – in the event of an emergency – NAS have no way of or responsibility for checking that the AED is present, accessible and/or operational.

The NAS shared registered CFR group location data with approval from the HSE with a total of 163 observations with three variables relating to CFR ID, town name and county were shared. Each observation was manually tagged to each Electoral Division code using the CSO Geo Hive Data. The CFR group data was coded to the specific town and if a town had more than one ED, then all EDs related to the town were tagged with a 1 to indicate CFR coverage. An example is Bray in Wicklow which has seven EDs therefore all seven were labelled with a 1 to indicate coverage. This resulted in a total of 233 Electoral Divisions with CFR coverage. This list includes only community-based CFR schemes that are linked to the NAS i.e. they could be activated by NAS ambulance control in the event of a cardiac arrest call. It does not include other first responders such as Garda, county fire service personnel or NAS off-duty responders.

The 2016 Census has a total of 802 variables within the census describing various aspects of the population relating to age, gender, housing, education, material ownership and socio-economic status. Each observation within the dataset is related to the 3,409 ED. This was merged with the OSI spatial data related to Ireland.

A database related to the road network was sourced from Geofabrik (2021) an open-source company that creates spatial data from OpenStreetMap. Geofabrik (2021) have created a road network with 26 types of roads including residential. The dataset was downloaded into a Spatial Lines Data Frame and filtered to the residential road network to identify residential clusters in Ireland.

Overview of Framework Method

Fig 1 indicates the framework method for this research indicating each stage starting with pre-processing the data, exploring the data to understand each component, model simulation applying Bayesian CAR models and MCLP and evaluation of the models.

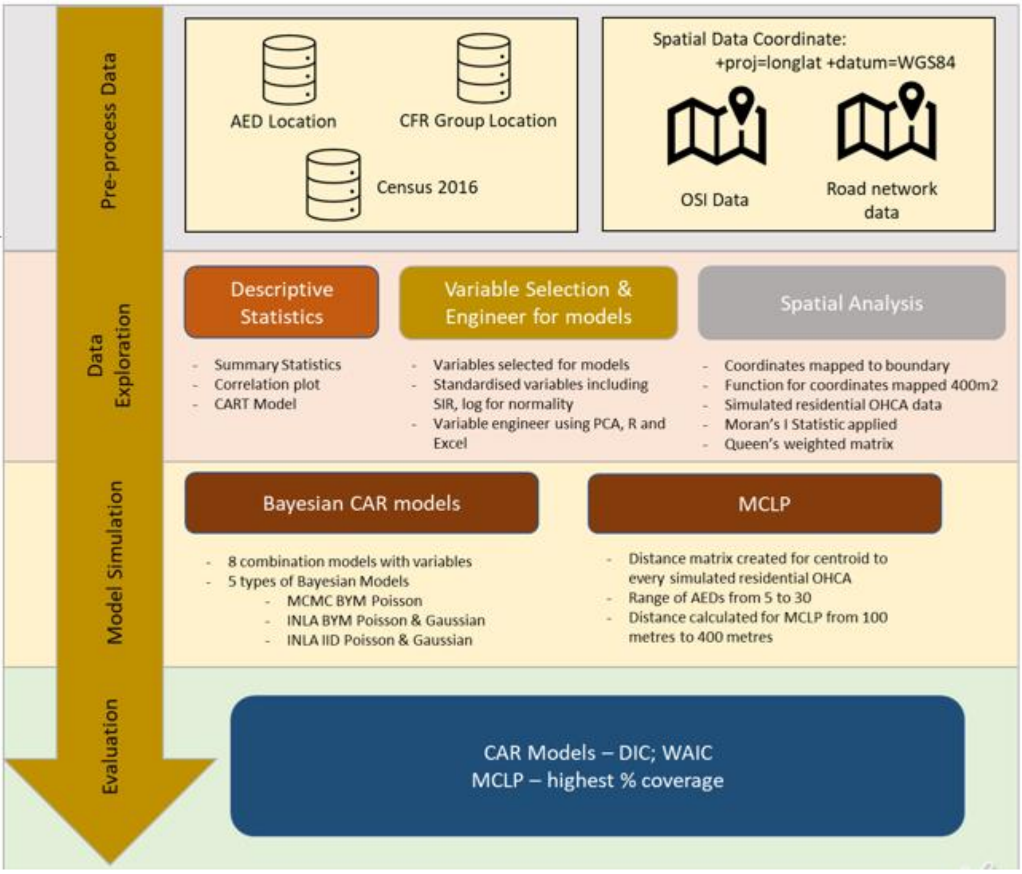

Fig 1. Framework Method. Visual of Framework method through each model stage.

Data Preparation & Analysis

Within the 2016 census there are two levels that indicate poor health 'very bad health' and 'bad health'; these were summed together, and indirect standardisation based on population per electoral division was applied to determine the expected rates of poor health per electoral division using 'SpatialEpi' library in R studio to produce the SIR ratio.

The age of the population per electoral division were standardised and split between 0-49 and 50 years, with an additional variable of age 50+ per percentage of the population to account for a 75% risk of OHCA which is of normal distribution (OHCAR, 2019), see Table 1.

Table 1. Summary Statistics Population of Engineered Variables from Census Dataset

Variable	Mean	Median	Min	Max
Bad Health	22.42	8	0	395

Age 0-49	372.5	409	34	32788
Age 50+	424.3	214	22	6106
Pop Total	1397	630	66	38894

A material deprivation covariate was calculated using variables from the 2016 census related to housing, employment, social status, and material ownership where each variable was standardised and applied to Principal Component Analysis (PCA). The selection of these variables was guided by the research of Masterson et al (2018) and Xia et al (2020).

The centroid coordinates were prepped of each electoral division were converted into latitude and longitude coordinates, and each 400m point was calculated in the direction of north, south, east, and west to the boundary border to simulate possible AED deployment locations. These points were then combined with the residential road network, and a point was mapped to represent every residential road within the electoral division boundary area to simulate OHCA data.

Spatial Smoothing

Bayesian Conditional Autoregression is a method to spatially smooth the data where EDs can borrow strength from neighbours and reduce randomness in variation. The use of MCMC can be computationally intensive and the use of INLA has been considered an alternative approach using Gaussian distribution (De Smedt et al, 2015). For the purposes of building a robust high risk area identification framework, a variety of models using two types of random effects Besag, York and Mollie (BYM) and 'IID' random effect model using MCMC (Masterson et al, 2018), INLA (Lin et al, 2016; Tierney et al, 2019), Poisson and Gaussian assumptions. All models had a burn in run of 10,000 iterations and 40,000 iterations retained (Masterson et al, 2018) using R Studio libraries 'INLA', and 'CARBayes. The SIR variable in each of these models was smoothed using a neighbourhood matrix using the Queen's method within 'GeoDA' software (Masterson et al, 2018).

The variables used within the model is the Y ~ 1 + offset(log(E)) where Y is the Observed and E is the expected poor health. This is a common method to model disease rates using Bayesian BYM (Duncan et al, 2019). For consistency across all models, the same log function was applied. The independent variables used were 0-49 and 50+ age, the percentage of 50+ aged population per ED and the High Deprivation variable derived from PCA. A total of 8 models were created using 5 different types of Bayesian CAR methods which totalled 40 models. The criteria for model selection are based on the lowest deviance information criterion (DIC).

Geographic Analysis

The self-assessed health variable was tested for spatial autocorrelation using the Global Moran's I statistic which was applied to all variables used within the Bayesian CAR methods. The hypothesis is:

H0: if the spatial data is randomly disbursed.

Ha1: a positive Z score meaning the data is spatially clustered.

Ha2: a negative Z score meaning the data is clustered in competitive way.

Geographic analysis was applied using a framework for AED deployment against hypothetical AED deployment using a 400-metre points to the boundary. This geographic spread of AEDs was measured against the residential road network, with the optimal coverage of AEDs to an OHCA on each residential road. This method ignores financial constraints to AED deployment and instead a framework for the optimal placement of AEDs using MCLP optimization method from Church and ReVelle (1974) in R Studio library 'Maxcovr'. (Tierney, 2019).

Design Specification

The Design Specification for this research is split into two parts within the framework 1) the identification of high-risk health areas and 2) a framework for AED deployment that can be applied to any area (Fig 2).

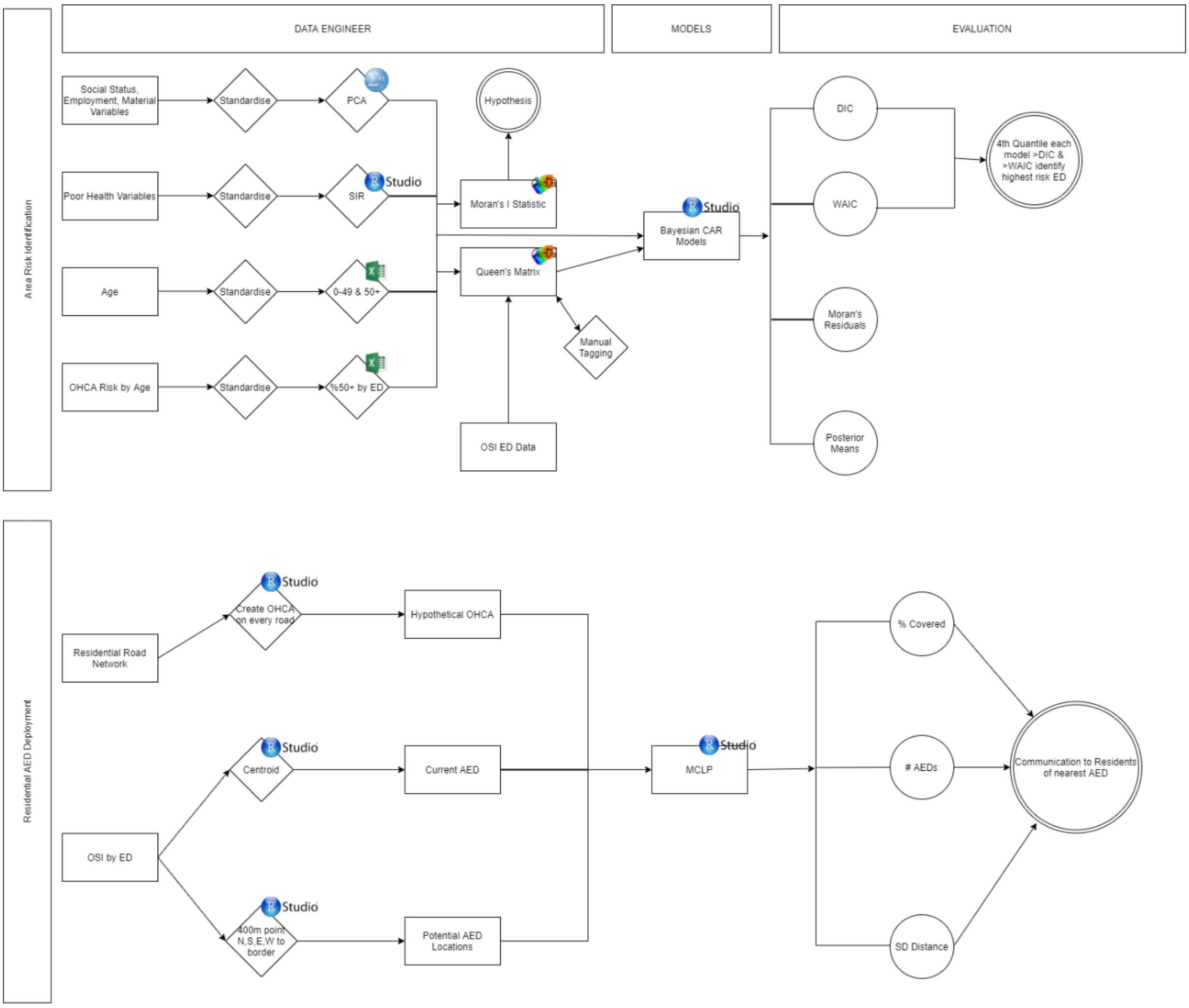

Fig 2. Design Specification. Visual of Design Specification indicating software and data flow.

The design implementation for high-risk health areas uses Bayesian CAR methods with a Poisson or Gaussian assumption, and MCMC or INLA. A total of 8 models will be tested against each type of 5 types of Bayesian CAR method, resulting in 40 models. The data will be further prepped for implementation and applied with the same burn in and run-in rates as Masterson et al (2018). Evaluation will be dependent on the most common high-risk areas which will be assessed by the lowest DIC and WAIC for each model type.

The framework for AED deployment will be calculated using the centroid as the current AED placement, with potential sites at every 400-metre point to the board in every compass direction. The potential OHCA cases will represent each residential road within the electoral division. This data will be overlayed using MCLP to calculate the distance and optimal number of AEDs per radius distance to OHCA point on a residential road. Evaluation will depend on the highest level of coverage (Metrot et al, 2019).

Results

Health Risk Identification Area

A total of 1.6% of the population classify their health as bad across a total of 3,328 Electoral Divisions. The age variable was split in Excel between 0-49 and 50+ with a total of 3.3 million and 1.4 million, respectively. This allows for the estimation of 75% of OHCA risk which is between 54 to 79 interquartile range. The percentage of 50+ per electoral division was also estimated to indicate levels of OHCA risk with a percentage ranging from 8% to 61%. This resulted in 70 electoral divisions with a 50+ population percentage of 50% or more.

The CART algorithm was applied to understand the relationship between High Material Deprivation, AEDs, and CFR groups (Fig 3). It was found in Root 1 – 1,570 EDs have low levels of High Material Deprivation, have no CFR group and no AED with 60.3% of EDs with a population of 30-40% aged 50+; Root 2 – 333 EDs have low levels of High Material Deprivation, no CFR group, but have an AED with 56.2% of EDs with a population of 30-40% aged 50+; Root 3 – 46 EDs have low levels of High Material Deprivation, have a CFR group, no AED with 37% of EDs with a population of 30-40% aged 50+; Root 4 – 62 EDs have low levels of High Material Deprivation, have a CFR group and have an AED with 50% of EDs with a population of 20-30% aged 50+; Root 5 – 1,035 EDs have high levels of High Material Deprivation, have no AED and no CFR group with 46.8% of EDs with a population of 30-40% aged 50+; Root 6 – 363 EDs have high levels of High Material Deprivation, have an AED and no CFR group with 53.2% of EDs with a population of 30-40% aged 50+.

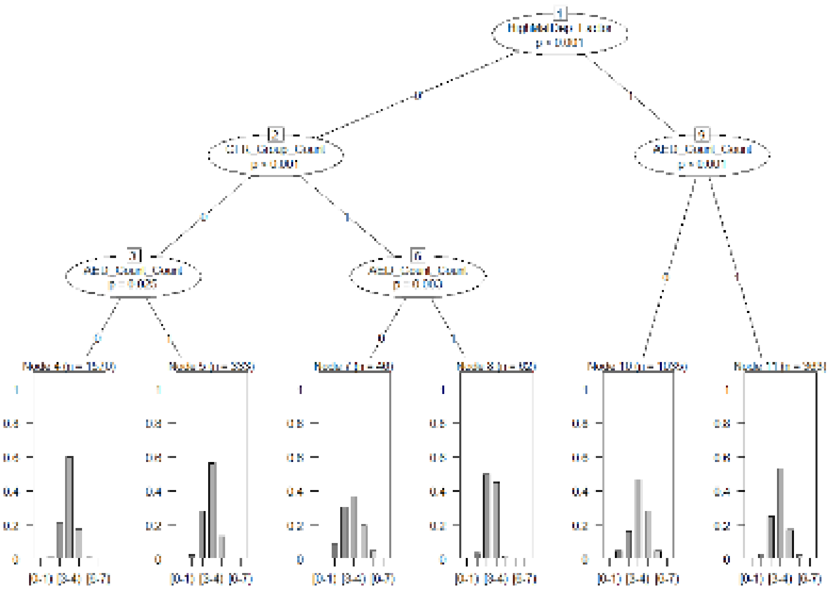

Fig 3. CART Algorithm. Illustration of relationship between material deprivation, AED, CFR groups and Age.

The unsmoothed SIR rate for the self-assessed health variable ranged from 0 to 8.73161 with a total of 206 areas with an incidence rate of 1 and above which is considered high levels of poor health per electoral division (Fig 4).

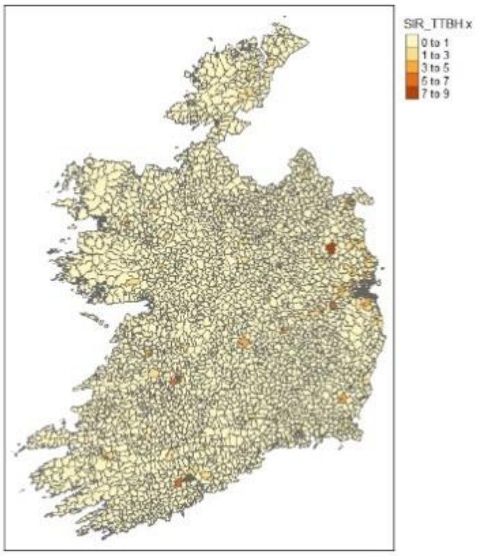

Fig 4. Unsmoothed SIR. SIR rate applied to poor health variable.

The standardised 35 variables were applied to PCA in SPSS V27 with a covariance matrix based on Eigenvalue greater than 1, with a varimax rotation and maximum iterations for convergence at 25. The test result of KMO 0.804 and Bartlett's test <0.05, indicating the dataset is a good fit for PCA. The PCA output were three components accounting for 86.91% of the variance: Component 1 Low Levels of Material Deprivation; Component 2 High Levels of Material Deprivation; and Component 3 relating to Agriculture. Component 2 was the covariate used in the CAR model which included 1) Housing: rented from local authority/voluntary/co-op housing; 2) Principal Status: looking for first job, unemployed and disability; 3) Social Status & Socio-Economic Group: semi-skilled, unskilled, and employed but unknown; 4) Ownership: no car, no pc, no broadband, and no internet. The newly created variable was merged in GeoDa with the spatial shapefiles from the OSI using the merge function and the GUID variable.

Univariate Moran's I statistic (Fig 5) was applied to the variables and covariates for the Bayesian CAR model with 999 permutations. All the variables had a score >0.05 both before and after the 999 permutations with a mean of -0.0003 to 0.0004, SD± 0.0101 – 0.0109 and a Z value ranging from 26.5580 to 43.8495. The results indicate a rejection of the null hypothesis in favour of Ha1 meaning the data is spatially clustered.

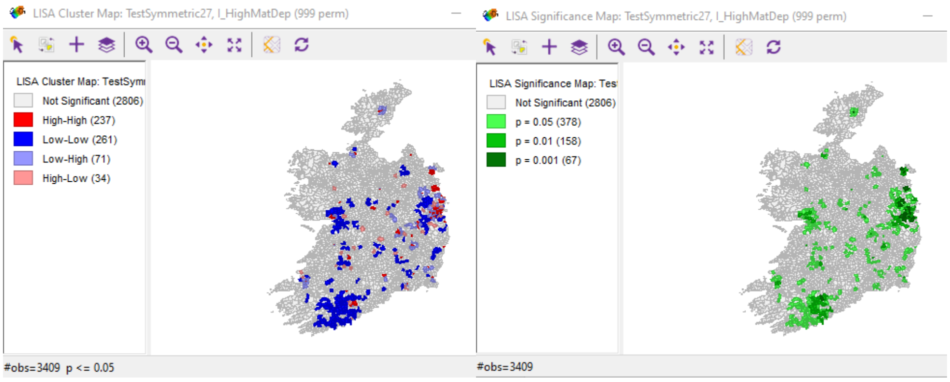

Fig 5. Moran's I Statistic. Illustration of application of Moran's I Statistic to High Material Deprivation variable created from PCA. The most significant areas for autocorrelation are the dark red on the left and dark green on the right.

The Queen's matrix was applied with 100 neighbours manually tagged with symmetry applied to ensure two-way neighbours (Fig 6). The islands were tagged to electoral divisions within the same county e.g., Arran Islands tagged to nearest Galway electoral divisions.

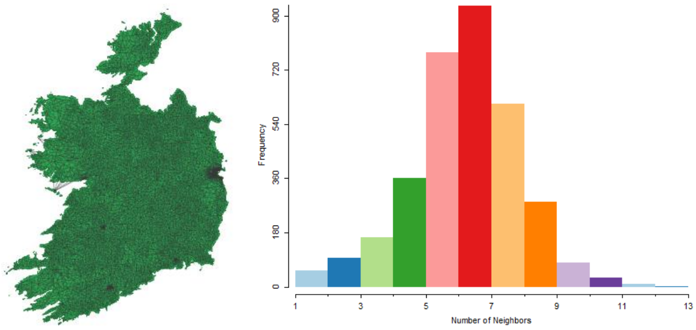

Fig 6. Queen's Matrix. Illustration of Queen's Matrix with a map of Ireland indication the relationship between each Electoral Divisions, and a histogram indicating the number of neighbours ranging from 1-13 with 6 as the median.

All the variables were applied to the Bayesian CAR models with various combinations resulting in 8 different model types (Table 2). There was about 600 DIC in the difference between the Poisson models with a larger difference in the Gaussian models. Table 4 illustrates the DIC per each Bayesian Autoregressive model for the observed self-assessed health variable. Of the 5 type of models applied the best fit are INLA Gaussian Random Effects with the single variable of % age of 50+ (Model 7) with a DIC of -10563.86 and a WAIC of -1709.59; the INLA Gaussian BYM model had a best fit with the single variable High Material Deprivation (Model 6) with a DIC of 13799.73 and WAIC of 13080.75; the INLA Poisson Random Effects model had the age variables (0-49 and 50+) as the best fit (Model 2) with DIC 20824.54 and WAIC of 20788.40; the INLA Poisson BYM model had the best fit of the age variables (0-49 and 50+) (Model 2) with a DIC of 20771.88 and WAIC of 20669.99; and the MCMC Poisson BYM model had the best fit of both age variables (0-49 & 50+) and the percentage of 50+ age of population (Model 4) with a DIC of 20088.855 and WAIC of 19561.413 (Table 2).

Table 2. Results table of the 40 models of Bayesian CAR with variation of Poisson, Gaussian, MCMC and INLA.

Models (CI 95)	**INLA Base Model Gaussian Random Effects**	**INLA BYM – Gaussian**	**INLA Base Model Poisson Random Effects**	**INLA BYM - Poisson**	**MCMC BYM - Poisson**
Model 1: Y ~ 1 + offset(log(E))	DIC: -8661.06 WAIC: -791.63 β: 17.727 (mean)	DIC: 34357.21 WAIC: 34338.35 β: 17.727 (mean)	DIC: 20980.38 WAIC: 21293.05 β: -7.183 (mean)	DIC: 20901.35 WAIC: 21013.02 β: -7.185 (mean)	DIC: 20365.91 WAIC: 19575.078 β: -2.4355 (median)
Model 2: Model 1 + log(Age)	DIC: 9819.63 WAIC: 10640.45 β: -148.315 (mean)	DIC: 31475 WAIC: 31532.02 β: -148.234 (mean)	**DIC: 20824.54 WAIC: 20788.40 β: -14.641 (mean)**	**DIC: 20771.88 WAIC: 20669.99 β: -14.644 (mean)**	DIC: 20089.408 WAIC: 19559.361 β: -7.4881 (median)
Model 3: Model 2 + High Mat Dep	DIC: -555.59 WAIC: 5938.89 β: -81.168 (mean)	DIC: 16565.46 WAIC: 15832.58 β: -81.160 (mean)	DIC: 20825.63 WAIC: 20789.53 β: -14.391 (mean)	DIC: 20772.91 WAIC: 20671.53 β: -14.509 (mean)	DIC: 20089.929 WAIC: 19562.274 β: -9.1418 (median)
Model 4: Model 2 + %50+	DIC: 7575.87 WAIC: 9036.62 β: -203.967 (mean)	DIC: 15062.96 WAIC: 15418.95 β: -203.475 (mean)	DIC: 20825.14 WAIC: 20788.94 β: -18.332 (mean)	DIC: 20772.61 WAIC: 20670.66 β: -15.817 (mean)	**DIC: 20088.855 WAIC: 19561.413 β: -12.4709** (median)
Model 5: Model 4 + High Mat Dep	DIC: 22744.84 WAIC: 24184.90	DIC: 15319.27 WAIC: 14443.90	DIC: 20826 WAIC: 20789.81	DIC: 20773.06 WAIC: 20672.01	DIC: 20094.840 WAIC: 19561.632 β: -10.9628

	β: -86.863 (mean)	β: -86.784 (mean	β: -17.442 (mean)	β: -15.425 (mean)	(median)
Model 6: Model 1+ High Mat Dep	DIC: -7603.38 WAIC: 119.44 β: 17.727 (mean)	**DIC: 13779.73** **WAIC: 13080.75** **β: 17.727 (mean)**	DIC: 20951.23 WAIC: 21162.47 β: -7.187 (mean)	DIC: 20885.02 WAIC: 20949.07 β: -7.186 (mean)	DIC: 20343.345 WAIC: 19626.606 β: -2.4304 (median)
Model 7: Model 1 + %50+	**DIC: -10563.86** **WAIC: -1709.59** **β: 68.167 (mean)**	DIC: 32628.72 WAIC: 32760.58 β: 52.616 (mean)	DIC: 20971.78 WAIC: 21265.32 β: -5.304 (mean)	DIC: 20897.13 WAIC: 20998.16 β: -5.783 (mean)	DIC: 20361.803 WAIC: 19585.880 β: -1.1192 (median)
Model 8: Model 7 + High Mat Dep	DIC: 30918.60 WAIC: 30939.48 β: 28.602 (mean)	DIC: 17192.38 WAIC: 16855.25 β: 28.602 (mean)	DIC: 20948.45 WAIC: 21155.84 β: -6.324 (mean)	DIC: 20883.41 WAIC: 20944.67 β: -6.479 (mean)	DIC: 203440.144 WAIC: 19623.057 β: -1.8288 (median)

The posteriors were calculated for each of the electoral divisions within the models and new variables were created to categorise the electoral divisions as high or low from the selected models. The high level was indicated by the 3rd quantile in the posteriors and anything below was classed as low (Fig 7). Table 3 indicates the difference in the number of High vs Low electoral divisions and the minimum and maximum posterior results per each model. Interestingly, in terms of Electoral Divisions that were high, the INLA models with the same assumption of Poisson or Gaussian, had a small difference in identified number of Electoral divisions considered high risk.

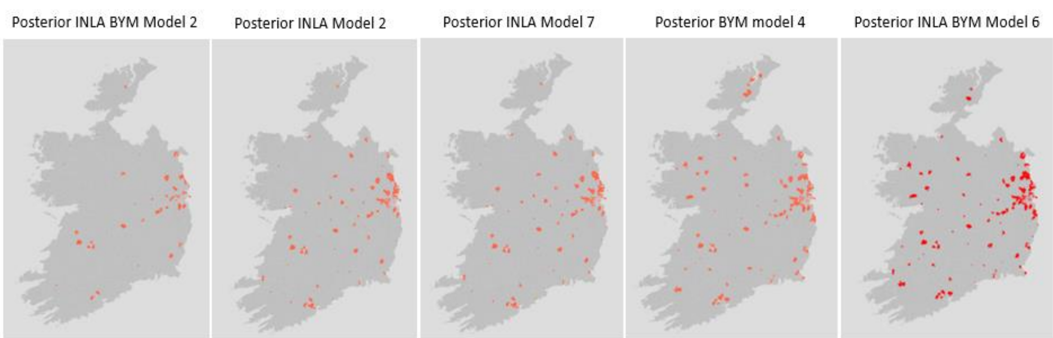

Fig 7. Posterior Means. Map illustration of each model with posteriors transformed using high and low with high in the 3rd quantile in red.

Table 3. Overall number of electoral divisions classed as high risk versus low risk

Models (CI 95)	SIR - Health	INLA Base Model Gaussian Random Effects	INLA BYM – Gaussian	INLA Base Model Poisson Random Effects	INLA BYM - Poisson	MCMC BYM - Poisson
Posterior High/Low (results)	High 206 Low 3203 (0/8.73)	High 66 Low 3343 (0.02/394.32)	High 65 Low 3344 (-0.001/ 394)	High 154 Low 3255 (0.002/8.73)	High 156 Low 3253 (0.002/8.7 3)	High 198 Low 3211 (0.32/396. 12)

Each of the selected models, were filtered to the category 'high' which resulted in a total of 56 electoral divisions classed equally as high risk (Table 4). Of the selected electoral divisions 22 have no registered AED with the EMS and no CFR group within the electoral division, these are considered the highest risk; followed by 19 areas with an AED but no CFR and 15 areas with a CFR group but no registered EMS AED.

Table 4. 56 common electoral divisions across all types of Bayesian CAR models

Common High Risk Electoral Divisions	County	AED Count	CFR Group	Age % 50+	High Material Dep	Population Total
Total ED: 56	Total County: 18	EDs with AED: 31	Yes: 15 No: 41	Min: 16% Max: 45%	Yes: 30 No: 26	Total Pop 56 EDs: 616,671
Cavan Urban	Cavan	0	Yes	28%	Yes	3770
Ennis Rural	Clare	5	No	28%	No	17709
Clenagh	Clare	2	No	28%	Yes	10299
Ballyglass	Clare	0	No	31%	No	5994
Ballincollig	Cork	0	Yes	29%	No	18621
Rathcooney	Cork	4	Yes	27%	No	8574
Bishoptown C	Cork	0	No	45%	No	4925
Letterkenny Rural	Donegal	1	No	26%	Yes	11398
Ballymun C	Dublin	0	No	25%	Yes	6112
Balbriggan Rural	Dublin	0	No	14%	Yes	16495
Airport	Dublin	0	No	18%	Yes	5018
Glencullen	Dublin	0	No	19%	No	19773
Kinsaley	Dublin	2	No	18%	No	9621

Swords-Forrest	Dublin	2	Yes	21%	No	15153
North Dock B	Dublin	0	No	17%	Yes	7695
Balbriggan	Dublin	0	No	27%	Yes	8116
Tallaght-Springfield	Dublin	1	No	24%	Yes	11012
Rush	Dublin	5	No	26%	No	9921
Blanchardstown-Coolmine	Dublin	0	No	23%	Yes	11320
Mountjoy A	Dublin	0	No	17%	Yes	5389
Blanchardstown-Abbotstown	Dublin	0	No	17%	No	6195
Blanchardstown - Blackestown	Dublin	0	No	16%	No	38894
Howth	Dublin	1	No	44%	No	8294
Beaumont B	Dublin	0	No	40%	No	4962
Firhouse Village	Dublin	0	No	21%	No	12214
Pembroke East D	Dublin	0	No	40%	No	5263
Clondalkin-Dunawley	Dublin	0	No	22%	Yes	11323
Castleknock-Knockmaroon	Dublin	0	No	25%	No	19027
Tuan Urban	Galway	1	No	35%	Yes	3511
Kilarney Urban	Kerry	5	Yes	38%	Yes	10826
Leixlip	Kildare	1	No	31%	No	15576
Droichead Nua Urban	Kildare	5	No	30%	Yes	7762
Naas Urban	Kildare	3	Yes	27%	No	21597
Kilcock	Kildare	0	No	19%	No	6930
Celbridge	Kildare	2	No	26%	No	15653
Morristownbiller	Kildare	1	No	22%	No	14781
Kildare	Kildare	0	No	24%	Yes	9874
Portlaoighise Rural	Laois	5	No	21%	Yes	16105
Ballysimon	Limerick	1	No	20%	No	13590
Ballycummin	Limerick	0	No	23%	No	18388
Longford Rural	Longford	3	Yes	28%	Yes	5704
Fair Gate	Louth	11	Yes	35%	Yes	10424
Dundalk Rural	Louth	13	Yes	25%	Yes	19265
Castlebar Urban	Mayo	0	No	37%	Yes	6163
Ballina Urban	Mayo	4	Yes	37%	Yes	4144
Ratoath	Meath	5	Yes	20%	No	11082
Julianstown	Meath	2	Yes	26%	No	10176

Navan Rural	Meath	0	Yes	21%	No	28117
Tullamore Urban	Offaly	18	No	31%	Yes	11437
Edenderry Urban	Offaly	5	Yes	22%	Yes	7001
Sligo North	Sligo	0	No	29%	Yes	5222
Nenagh West Urban	Tipperary	1	No	30%	Yes	5481
Carrick-on-Suir Urban	Tipperary	2	No	35%	Yes	4398
Roscrea	Tipperary	12	Yes	31%	Yes	6305
Wexford No. 2 Urban	Wexford	1	No	39%	Yes	4087
Enniscorthy Rural	Wexford	6	No	29%	Yes	9985

Residential AED Deployment

An electoral division was selected that had a high SIR rate which was selected prior to the completion of the 40 models in the previous section. The purpose was to illustrate proof of framework in an electoral division that could easily be deployed to each high-risk area to determine the most optimal AED deployment. The selected Electoral Division was Birr in County Offaly (Fig 8).

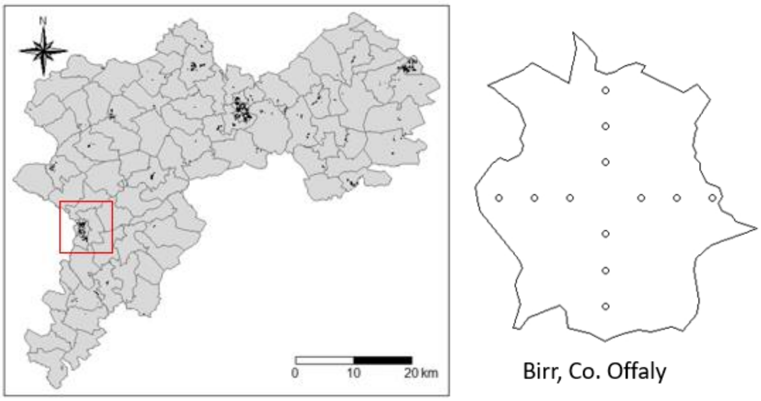

Fig 8. Birr, Offaly. Left image indicates the position of Birr and the residential road network overlayed by electoral divisions. The right image illustrates the points selected from the centroid to the boundary by every 400 metres.

Fig 3 illustrates each data point for distribution of potential location of AEDs with a radius of 200 metres (green), the 'current' AED with a 200-metre radius (orange) and hypothetical OHCA with a marker placed on each residential road (small blue dots). MCLP was implemented using the 'Maxcovr' package in R testing the distance of 100 metres to 400 metres for AED. A minimum of 95.61 metres was the nearest OHCA to the centroid. The furthest distance was 1.47 kilometre. With 1 AED placed at the centroid of the Electoral Division there is a total of 1 OHCA covered, and 55 points not covered or 98% not covered with an average distance of 731 metres for each OHCA with a SD of 312.

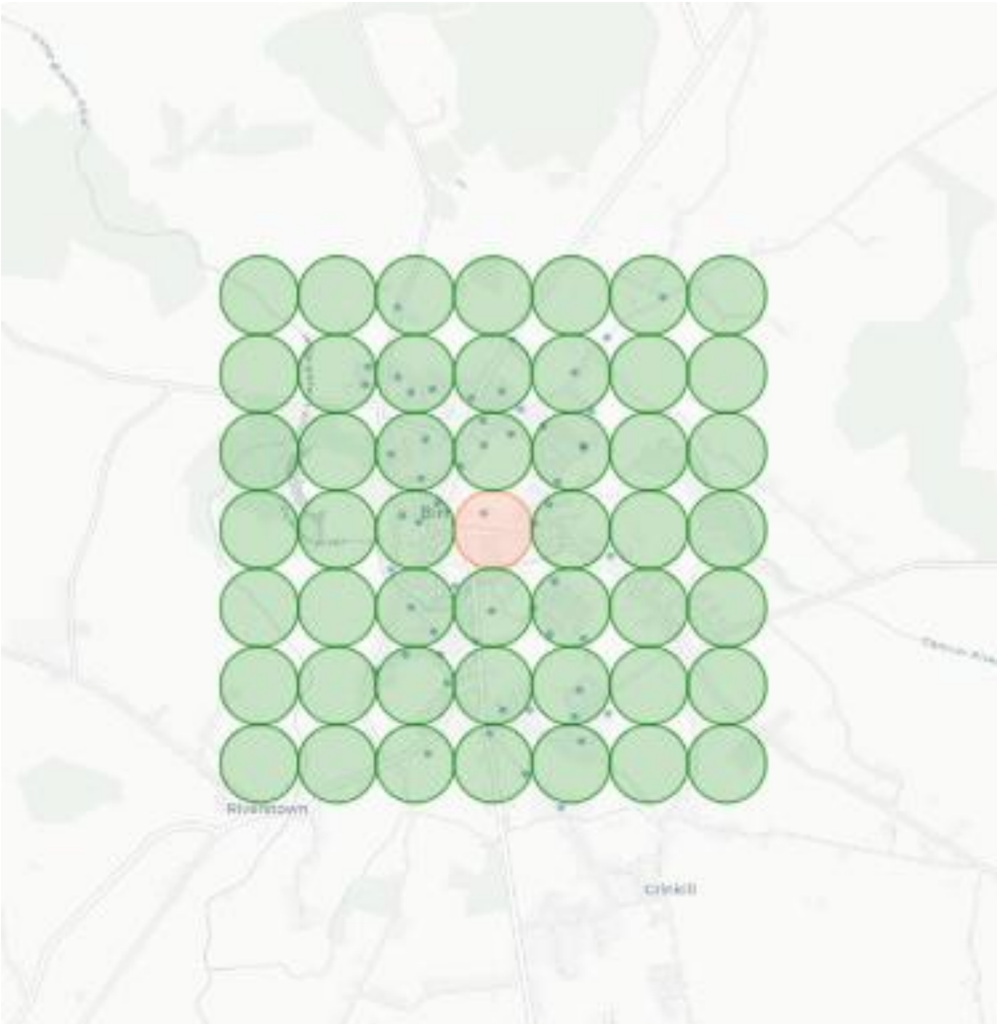

Fig 9. AED Potential Locations. Illustration of the selected OHCA events (blue), potential AED Locations with radius (green) and the centroid as the current AED placement (orange).

Table 5 indicates the results from each of the runs ranging from 100 metres to 400 metres. Model selection (*) is based on the % of OHCA covered with the least number of AEDs.

Table 5. MCLP results of potential AED coverage across residential OHCA

AEDs Added	# OHCA Covered	# OHCA Not Covered	% Covered	Mean Distance	SD Distance
Distance: 100 metres					
5	8	48	14.3%	320	193
10	13	43	23.2%	273	205
15*	15	41	26.8%	195	124
20	15	41	26.8%	184	106

25	15	41	26.8%	166	83.1
30	15	41	26.8%	166	83.1
Distance: 150 metres					
5	13	43	23.2%	468	371
10	18	38	32.1%	227	135
15*	23	33	41.1%	176	99.4
20	23	33	41.1%	173	98.6
25	23	33	41.1%	162	79.6
30	23	33	41.1%	162	79.6
Distance: 200 metres					
5	19	37	33.9%	377	261
10	31	25	55.4%	236	162
15	40	16	71.4%	192	142
20*	45	11	80.4%	148	62.7
25	45	11	80.4%	148	62.7
30	45	11	80.4%	148	62.7
Distance: 300 metres					
5	32	24	57.1%	305	180
10	47	9	83.9%	214	119
15	54	2	96.4%	174	90.3
20*	56	0	100%	160	73.1
25	56	0	100%	157	71.4
30	56	0	100%	151	65.3
Distance: 400 metres					
5	45	11	80.4%	309	145
10*	56	0	100%	230	100
15	56	0	100%	196	93
20	56	0	100%	254	98.9
25	56	0	100%	221	99.8
30	56	0	100%	212	99.7

Discussion and Conclusion

Identification of High Risk OHCA Areas Model Result Discussion

The variety of models presented in this paper illustrate how the type of Bayesian CAR model can influence results when the same variety of variables are applied. It appears that in terms of this data the basic 'IID' model with a Gaussian assumption performs best when comparing DIC and WAIC results to the BYM models and Poisson assumption. The BYM and Poisson assumption models have a DIC of >10000 with the random effects with Gaussian assumption with the lowest DIC. However, the choice of Bayesian model illustrates the various fit of models which resulted in 7, 6, 2 and 4. When comparing the DIC and WAIC it appears the Poisson models had similar results, while the Gaussian random effects and BYM model had a greater difference. Of the best fit models, two had a covariate each relating to Material Deprivation (model 6) which indicates similar findings of deprivation to Masterson et al (2018) and Xia et al (2020).

Comparative Bayesian Risk Analysis

This framework illustrates how a combination of Bayesian spatial smoothing models can identify a subset of the highest at-risk areas for AED deployment. The novel use of comparative models between Gaussian and Poisson assumptions, and MCMC and INLA, allows a more robust indication of the highest at-risk areas. Other research has compared MCMC and INLA, finding that INLA is a good alternative to MCMC (Smedt et al, 2015), a finding also within this research were the DIC and WAIC between INLA and MCMC models are similar.

From this research it appears that when considering risk using Bayesian spatial smoothing regression models, it appears that the choice of model can impact on risk assessment and when the risk reflects the well being of the population or the model has a direct impact on well-being, a robust comparative framework using more than one Bayesian model is a good method to compare the smoothing of areas. The comparison of Bayesian models within this paper demonstrated 56 electoral divisions as the highest risk, of these 22 have no AED and no CFR group thus indicating a comparative robust framework for risk analysis.

Local Smoothing Vs Global Smoothing

There appears to be no Bayesian CAR models within the domain of identification of high-risk health areas using the localised smoothing method, such as Bayesian CAR dissimilarity model (Lee & Mitchell, 2012), as opposed to the methods used in this paper, global smoothing. It is possible within the models in this paper that localised nuances of risk have been missed due to the global spatial smoothing function. Global spatial smoothing models have been found to 'over smooth' data (Crumb et al, 2017). It is possible that applying a localised spatial approach may yield different and more insightful results between the variables particularly the material deprivation variable.

Residential AED Deployment Result Discussion

Due to limited computational issues, all 56 of the highest risk areas based on evaluation of in section 6.1, could not be implemented due to computational limitations. Instead, a prior model created before all Bayesian Models were created is used as proof of concept for AED deployment framework using the electoral division of Birr in County Offaly.

The model range of AEDs deployed is 10 – 20 depending on distance coverage for OHCA. The most optimal is 20 AEDs at 300 metres with 100% coverage of all simulated OHCA points in the residential area, however this true number of AEDs could fall between 16-20. When the distance is expanded to 400 metres 100% coverage of the OHCA points is reached with 10 AEDs.

This framework is a simple evaluation tool to determine the number of AEDs to cover a residential area based on optimal distance. This tool is similar to Metrot et al (2019) were a random selected points of potential AEDs and random OHCA across the city of Beirut. In contrast the model presented in this paper aimed to specifically generate coverage for residential areas within an electoral division and incorporating distance to travel to secure an AED. The distance and residential coverage are missing from Metrot et al (2019).

The maximum result achieved in Metrot et al (2019) was a coverage of 93.07% of the total population with an unknown distance metric for retrieval of AED. It appears when considering residential against distance, this model can achieve 100% coverage.

MCLP AED Deployment & Communication

This framework is a simple evaluation tool to determine the number of AEDs to cover a residential area based on optimal distance. This tool is similar to Metrot et al (2019) were a random selected points of potential AEDs and random OHCA across the city of Beirut. In contrast the model presented in this paper aimed to specifically generate coverage for residential areas within an electoral division and incorporating distance to travel to secure an AED. The distance and residential coverage are missing from Metrot et al (2019).

However, applying MCLP within the framework an indication of the average coverage, but as indicated by Ringh et al (2019) the most important feature is the ability for an AED to reach an OHCA within a 3-minute round trip. As mode of transport is unknown and geographic features (incline, obstacles etc.) within this model, the distance of 100metres to 400 metres, allows for the model to be altered based on specific residential features. Therefore, in line with recommendations (Ringh et al 2018; Masterson et al 2018), the placement, distance, and preferred mode of transport to retrieve an AED must be communicated with each of the residents within the area for optimal coverage. It is suggested that if this framework is implemented, communication methods are advised to be applied to encourage retrieval and knowledge of AED placement. An example is a point-of-sale item such as a keyring or a fridge magnet that specifies the location of the nearest AED, distance, time to retrieve and optimal mode of transport on the item.

Conclusion

This paper identified a novel framework for identification of high-risk health areas and an approach to AED deployment within a residential area, a recognised gap within the domain of AED deployment (Moran et al, 2015; Ringh et al, 2018). Implementation of this approach could strengthen the chain of survival within each high-risk electoral division and can illustrate the level of coverage required to achieve 100% AED coverage within an area.

It is recommended for future work to deploy this model on the entire residential database for Ireland and determine what the most optimal coverage of the highest risk electoral divisions are, and for other electoral divisions. However, there were computational issues applying MCLP to a greater number of Electoral Divisions using the road network as a proxy. It is also suggested for future work to consider the model against historical OHCA data to determine if the 56 electoral divisions identified have had OHCA event in the past 5 years. It is also a suggestion for future work to deploy this model to the public and allow residents to calculate the optimal placement for AED and the risk score for the area. This is a model that could also highlight the benefits of having a registered EMS AED in the area and encourage the creation of a CFR group. This is perhaps a consideration for the HSE to undertake to drive awareness with the public.

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