Appendices

Appendix A. Statistical Methods

A.1. Models

We utilized Bayesian hierarchical models to combine data from all trials while accounting for the variation of survival times, or rehospitalization indications, within and between studies. One important feature of the Bayesian hierarchical models is that, because they allow for borrowing of information across studies/subgroups, they allow us to make inferences about subgroups that may be under-represented in a subset of the trials. Moreover, missing values are treated as additional variates whose values can be naturally imputed as part of the estimation procedure with Markov Chain Monte Carlo methods.^{1, [2](#page-10-1)}

The Bayesian paradigm requires specification of both the likelihood for the observations as well as priors for the model parameters. Preliminary analysis of the survival data from all trials indicated that the Weibull parametric survival model adequately fit the survival data, in particular, with results similar to those obtained under the Cox-Proportional Hazards Model. We thus utilized the Weibull parametric survival model to time to death from all causes. Under this model, we formulate the hazard function for an individual observed in study as:

(1)

where is the baseline hazard function in study . We assumed that , that is, the hazard function from a Weibull distribution with shape parameter and scale parameter

. Furthermore, refers to treatment, refers to age, and the vector with the remaining covariates for subject . We are interested in investigating whether the efficacy of ICD relative to usual care is modified by age and thus we also include an interaction between treatment and age. The above formulation allows for trial-specific baseline hazard functions, as well as trial-specific

main effects of treatment. This formulation allows us to account for the possible heterogeneity in treatment effect or in the underlying risk of death from all causes between patients in the different trials. Furthermore, allowing for random effects addresses the correlated nature of the data in its multi-level resolution with patients clustered within trials. To allow for borrowing of information, we assumed that:

(2)

We completed the model formulation with the following priors:

(3)

that is, we assumed non-informative priors for the population (mean) parameters. Moreover, we assumed that for the variance components,

In our applications, we utilized These values were chosen to be minimally informative and such that, the preliminary analysis of simpler Bayesian hierarchical models (e.g. only random effects for treatment effect or only trial-specific baseline hazard functions), resulted in similar inference to those from the frequentist Cox-proportional hazards model.

We formulated a model for the indicator of at least one rehospitalization by analogy. Let denote the probability that individual had at least one rehospitalization. Then, we assumed

(4)

with a hierarchical formulation similar to that described by equations (2)-(3).

 Variations of the above models were formulated to address specific sensitivity analysis. All models were estimated using Markov Chain Monte Carlo (MCMC) methods with Winbugs.

A.2. Missing Data

Let denote a particular covariate with missing value (for example, that $QRS > 120$) for an individual in trial . To allow for imputation of missing values, we assume that each covariate follows a Bernoulli model. Specifically, let denote the probability of the event defined by the covariate in trial . We assume that and that, a priori, The above model implies that each missing covariate value is imputed via simulation prediction within each iteration of the MCMC procedure. Thus the procedure incorporates the uncertainty on the missing value.

A3. Posterior Inference

Under the Weibull proportional hazards and logistic regression models (1)-(4) there are natural measures of treatment effectiveness as given by the hazard ratio and odds ratio, respectively. To assess the "significance" of the interaction parameter , in analogy to p-values that are attained under frequentist analyses, we computed the two-sided posterior tail probability of no interaction which is . When the two-sided posterior tailed probability of no interaction was less than 0.05 we concluded that there was

enough evidence for an interaction between treatment and age.

To graphically represent the overall treatment effect as dependent on age (that is, to interpret the interaction), we evaluated the hazard ratio comparing "typical" individuals in the same trial, with the same covariate values for X and W, but differing with respect to treatment, that is, receiving ICD versus usual care. In this calculation we replaced the study-specific treatment effect with the overall treatment effect so that the heterogeneity in treatment effects across trials is accounted for. Thus, we obtained the following expression:

The above expression is a function of W, that is, age only. Thus, to obtain Figure 4, we use posterior samples of and evaluate expression (3) above – thus, obtaining posterior samples of the hazard ratio evaluated at any given age W. We do the same for a range of values of W. The posterior samples are then summarized. We use the posterior median value of the hazard ratio at each given age as the point estimate and the 95% posterior credible intervals are obtained by computing the 2.5 and 97.5 quantiles of the posterior samples.

Appendix B. Supplementary Tables

Supplementary Table 1. Baseline Characteristics Stratified by Trial

ICD indicates implantable cardioverter-defibrillator and IQR interquartile range.

*Data are presented as % unless otherwise indicated and are based on patients with available data.

Supplementary Table 1 (continued).

ICD indicates implantable cardioverter-defibrillator and IQR interquartile range.

*Data are presented as % unless otherwise indicated and are based on patients with available data.

Supplementary Table 2. Baseline Characteristics Stratified by Sex

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ICD indicates implantable cardioverter-defibrillator and IQR interquartile range.

*Data are presented as % unless otherwise indicated and are based on patients with available data.

References

- 1. Schafer JL. *Analysis of Incomplete Multivariate Data*: Chapman & Hall/CRC; 1997.
- 2. Little RJA and Rubin DB. *Statistical Analysis With Missing Data, Second Edition*: Wiley-Interscience; 2002.