dependent covariate process $X(t)$ observed till death T that is subject to right censoring by lost to follow-up. In this setting CAR is equivalent to the assumption that the conditonal cause-specific hazard of censoring at each t depends on X only through the past $\{X(u); 0 \leq u \leq t\}$. Robins and Rotnitzky (1992) used their methodology to construct locally efficient estimators of the marginal survival function of T and of regression parameters in the Cox-proportional hazards model and accelerated failure time model for the law of T given baseline covariates Z. The authors showed that their locally efficient general estimating function methodology allowed them to both (i) correct for any bias due to informative censoring attributable to the covariate process $X(t)$ and (ii) to recover information from the censored observations by nonparametrically exploiting the correlation between the process $X(t)$ observed up to the censoring time and the unobserved failure time T. Additional papers by these authors and colleagues considered multivariate regression models for repeated measure outcomes and median regression models for failure time outcomes subject to right censoring and/or missing regressors. (Robins, 1993a, 1996, Robins and Rotnitzky, 1992, 1995b, 1996, Robins, Rotnitzky and Zhao, 1994, 1995, Rotnitzky and Robins, 1995a,b, Robins, Hsieh, Newey, 1995, among various other references) . Robins, Rotnitzky and Zhao (1995), Robins and Rotnitzky (1995), Robins and Wang (1998), and Robins and Gill (1997) considered CAR data with non monotone missing data patterns.

The Robins-Rotnitzky locally efficient estimating function methodology has recently been used to solve a number of interesting statistical problems. Pavlic, van der Laan and Buttler (2001) estimated the parameters of a multiplicative intensity model and of a proportional rate model in the presence of informative censoring attributable to time-dependent covariates that were not included as regressors in the models. Quale, van der Laan and Robins (2001) constructed locally efficient estimators of a multivariate survival function when failure times are subject to failure-time-specific censoring times which required iteratively solving an integral equation that did not admit a closed form solution. In this same setting, but including time-dependent covariate processes in the observed data structure, Keles, van der Laan, and Robins (2002) proposed closed form estimators that are easier to compute and almost as efficient as the Quale et al. iterative estimator. Van der Laan, Hubbard, and Robins (2002) constructed locally efficient closed-form estimators of a a multivariate survival function when the survival times are subject to a commom censoring time. Van der Laan, Hubbard (1998, 1999), building on Hu, Tsiatis (1996), and Zhao and Tsiatis (1997) constructed locally efficient estimators of (i) a survival function from right censored data subject to reporting delays and (ii) the quality-adjusted survival time distribution from right-censored data. Strawderman (2000) and Bang and Tsiatis (2002), respectively, used the Robins-Rotnitzky methodology to estimate the mean of an increasing stochastic process parameters and the parameters of a median regression model for medical costs from right censored data. Datta, Satten and Datta (2000) used the methodology to estimate a three state illness-death model from right censored data.

The Robins and Rotnitzky (1992) methodology was later extended to censored data structures in which the full data on a subject are never observed. Van der Laan and Hubbard (1997), Van der Laan and Robins (1998), Andrews, Van der Laan and Robins (2000), and van der Laan (2000) considered estimation of the marginal survival function of T and of regression parameters of an accelerated failure time model for the law of T given baseline covariates Z from current status and/or interval censored data structures wherein the failure time variable T is never exactly observed but the intensity function for monitoring whether failure T has occured by time t depends on the observed history $\{X(u); 0 \leq u \leq t\}$ of a multivariate covariate process.

Robins (1993b, 1998b, 1999) extended the methodology of Robins and Rotnitzky (1992) to estimate the parameters of longitudinal counterfactual causal models under a sequential randomization assumption (SRA) by exploiting the fact that counterfactual causal inference is formally a missing data problem (Rubin, 1978). The full data structure X is the set of counterfactual treatment-specific responses indexed by the set of potential treatments. The observed data structure Y consists of the actual treatment received and its corresponding treatment-specific response. Because only one of the potential treatments is actually received, X is never fully observed. The SRA is the assumption that the conditional probability of receiving a particular treatment at time t may depend on past treatment and response history but does not further depend on the unobserved counterfactual responses. Robins, Rotnitzky, and Scharfstein (1999) showed that, under fairly general conditions, the SRA is equivalent to CAR and extended the Robins and Rotnitzky (1992) general estimating function technology to this causal inference missing data problem. Because many readers may be less familiar with the causal inference literature than with the censored or missing data literature we provide some useful references. Rubin (1978), Rosenbaum (1984, 1987, 1988), Rosenbaum and Rubin (1983, 1984, 1985) and Robins, Mark, Newey (1992) consider causal inference for time-independent treatments. Robins (1989a,b, 1992, 1994, 1998a,b,c, 1999) introduces structural nested and marginal structural models for the causal effect of time-dependent treatments from longitudinal (panel) data and provides a locally efficient estimating function methodology . Hubbard, van der Laan, Robins (1999) develop closed form locally efficient estimators of treatment specific survival functions right-censored data. Mark, Robins (1993), Robins, Greenland (1994), Hernan, Brumback, Robins (2000), Henneman and van der Laan (2002), Bryan, Yu and van der Laan (2002), Yu and van der Laan (2002) apply this methodology to (re)analyze a number of interesting data sets .

In this book, we review the aforementioned developments and further generalize the general estimating function methodology to cover any CAR