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Economic Evaluation

Flexible Approaches Based on Multistate Models and Microsimulation to Perform Real-World Cost-Effectiveness Analyses: An Application to Proprotein Convertase Subtilisin-Kexin Type 9 Inhibitors

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ABSTRACT

Objectives: This study aims to show the application of flexible statistical methods in real-world cost-effectiveness analyses applied in the cardiovascular field, focusing specifically on the use of proprotein convertase subtilisin-kexin type 9 inhibitors for hyperlipidemia.

Methods: The proposed method allowed us to use an electronic health database to emulate a target trial for cost-effectiveness analysis using multistate modeling and microsimulation. We formally established the study design and provided precise definitions of the causal measures of interest while also outlining the assumptions necessary for accurately estimating these measures using the available data. Additionally, we thoroughly considered goodness-of-fit assessments and sensitivity analyses of the decision model, which are crucial to capture the complexity of individuals' healthcare pathway and to enhance the validity of this type of health economic models.

Results: In the disease model, the Markov assumption was found to be inadequate, and a "time-reset" timescale was implemented together with the use of a time-dependent variable to incorporate past hospitalization history. Furthermore, the microsimulation decision model demonstrated a satisfying goodness of fit, as evidenced by the consistent results obtained in the short-term horizon compared with a nonmodel-based approach. Notably, proprotein convertase subtilisin-kexin type 9 inhibitors revealed their favorable cost-effectiveness only in the long-term follow-up, with a minimum willingness to pay of 39 000 Euro/life years gained.

Conclusions: The approach demonstrated its significant utility in several ways. Unlike nonmodel-based or alternative model-based methods, it enabled to (1) investigate long-term cost-effectiveness comprehensively, (2) use an appropriate disease model that aligns with the specific problem under study, and (3) conduct subgroup-specific cost-effectiveness analyses to gain more targeted insights.

Keywords: cost-effectiveness, electronic health records, microsimulation, real-world data, target trial emulation.

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Highlights

- Cost-effectiveness analysis utilizing electronic health records databases can offer valuable real-world evidence for drugs recently approved. However, the statistical aspects of economic-health evaluations in chronic illnesses using decision models are often overlooked.
- We proposed the application of a flexible multistate decision model based on microsimulation to replicate a target trial using observational data, enabling the study of proprotein convertase subtilisin-kexin type 9 inhibitors cost-effectiveness. Notably, these methods overcome the limitations of standard Markov decision models by considering the dependence of individuals' healthcare paths on their past.
- This study provides novel insights into the real-world cost-effectiveness of proprotein convertase subtilisin-kexin type 9 inhibitors in hyperlipidemia. Furthermore, the statistical approach used here could also be useful for other diseases, treatments, or healthcare systems.

Introduction

Economic evaluation to predict the cost-effectiveness (CE) profile and the financial consequences of adopting interventions for the healthcare system are of increasing importance as life expectancy, prevalence of chronic diseases, and costs for innovative treatments are rising. Such analyses are typically based on data gathered from randomized clinical trials (RCTs). However, RCTs have several limitations, and strict enrollment criteria partially limit regulatory agencies in rules for real-world populations.[1,2] Indeed, the efficacy observed in premarketing studies may be quite different from the effectiveness in clinical practice because of the following reasons: (1) frail patients are usually excluded from RCTs, (2) trials are carried out in controlled environments, whereas patient's low drug adherence and therapeutic inertia are common in real practice, and (3) the short length of follow-up limits the assessment of long-term treatment benefits (and harms).

The attention of medical research for retrospective observational studies, especially those based on electronic health records or healthcare utilization databases (EHR), has progressively increased. Because all health services provided to the patients are included in these databases, the complete care pathway experienced by subjects can be identified, including clinical outcomes and healthcare costs. Therefore, EHR can be used to assess the impact of drugs introduced into the market in terms of the

effectiveness of the treatment in reducing the progression of the disease for which they are prescribed and CE profile in specific areas and populations.[3] Therefore, these data sources have the potential to enable more targeted and area-specific public health interventions.

However, statistical challenges in performing such analyses are the identification of appropriate methods to (1) consider the observational nature of data, (2) model health outcomes and cost in a complex time-to-event framework, and (3) integrate methods for health economic evaluations. Decision models are common choices in economic evaluations to perform a comparison between competing decisions under uncertainty. Although these models are usually adopted to perform CE analyses based on data derived from RCTs, they are less applied in studies based on real-world data (RWD).

Methods for CE can be broadly categorized into nonmodel-based and model-based approaches. Nonmodel-based approaches are useful for describing the current situation using available data. However, for formal comparisons and predictions of alternative treatment strategies, model-based methods are necessary, especially when generalizability to larger populations, lifetime scenarios, or focus on specific subgroups is desired.

Model-based methods can be further divided into cohort models and individual-level (microsimulation) models.[4,5] Cohort models are commonly used in health economics. However, they may not capture the complexities of real healthcare system mechanisms because they often assume Markovianity and time homogeneity, which may not hold. On the other hand, microsimulation models generating individual life-course trajectories between health states are more flexible in taking into account in the subjects' temporal dynamics.

The application that motivated our work is the study of CE of antibodies that inhibit proprotein convertase subtilisin-kexin type 9 (PCSK9-I). These are a new class of drugs that lower low-density lipoprotein (LDL) levels, preventing major cardiovascular events. The majority of the evidence in terms of the risk-benefit profile and economic-health assessments on the use of PCSK9-I is based on RCTs.[6-8]

The main objectives of this study are to (1) present flexible statistical approaches to real-world CE analyses, (2) show how state-of-the-art multistate methods can be combined to microsimulation to build a framework able to generate reliable and timely evidence of the sustainability of drug treatments, (3) combine target trial emulation techniques to limit the danger of biases due to nonrandomization, and (4) perform a CE analysis for the addition of PCSK9-I to lipid-lowering therapy (LLT) in patients with hyperlipidemia from the payer perspective.

Methods

Study Design and Target Trial Emulation

Observational data from an Italian EHR is used to emulate a target trial for individuals eligible to the use of PCSK9-I according to the criteria established by the Italian Medicines Agency. To emulate a target trial, it is necessary to develop a comprehensive protocol that outlines the fundamental design and analytical elements of the study (ie, eligibility criteria, treatment strategy, assignment procedures, outcomes, follow-up period, causal contrast of interest, and statistical analysis).[9-11] A summary of the components of the emulated trial's protocol for studying the cost-effectiveness of PCSK9-I is given in Table 1, together with the mitigation strategies used to address challenges in using EHR and potential sources of bias.

Data Sources

The study is conducted using data from the Observatory of Cardiovascular Diseases of the Friuli-Venezia Giulia region[12] that systematically collects integrated administrative and cardiological clinical data that refer to the Trieste and Gorizia area (366.732. inhabitants). In Italy, all residents have equal access to health care by the National Health Service. The data sources interrogated for the present work are the Registry of Births and Deaths, Hospital Discharge data, Public Drug Distribution System, Exemption codes, cardiological e-chart (C@rdionet), and examination results of public laboratories. According to the current Italian law, the study protocol was approved by the Unique Regional Ethics Committee Friuli-Venezia Giulia, with Protocol ID 185_2022.

Notation and Estimand of Interest

Let P be the treatment strategy indicator for the use of PCSK9-I, D the time to death and C the time to administrative censoring. Censoring time is assumed to be noninformative. The observation time is $Y^D = \min(D, C)$ and $\delta^D = I(Y^D = D)$ is the event indicator. We also denote by $M(W)$ the total medical costs up to a time horizon W. Because of death and censoring, the observed values related to the cost accrued up to time W that can be observed are $Y^W = \min(M(W), M(D), M(C))$. We let $M^H(w) = \{M(u), u \leq w\}$ be the intermediate cost history where $M(u)$ is the observed accumulated cost up to time u.

We also define $D^{(P)}$ as the potential timing for the terminal event under the binary treatment strategy P and $M(W)^{(P)}$ the potential medical cost accumulated up to time W under the treatment strategy P.

The quantity of interest is the incremental cost-effectiveness ratio (ICER) at a time-horizon w defined as follows:

$$ICER(w) = \frac{E\left[M(w)^{(1)} - M(w)^{(0)}\right]}{E\left[f\left[min\left(D^{(1)}, w\right)\right] - f\left[min\left(D^{(0)}, w\right)\right]\right]} \quad (1)$$

Note that $E[\,min(D^{(P)}, w)]$ are the mean Life Years (LY) over a time horizon w and $f(\cdot)$ denotes a generic function of the LY to encompass measures of quality of life, such as quality-adjusted life years (QALY).

Moreover, as a further objective, we are interested in estimating a subgroup-specific ICER:

$$ICER_x(w) = \frac{E\left[M(w)^{(1)} - M(w)^{(0)} | X = x\right]}{E\left[f\left[min\left(D^{(1)}, w\right)\right] - f\left[min\left(D^{(0)}, w\right)\right] | X = x\right]} \quad (2)$$

in which x defines eligibility subgroups as explained in the Supplemental Materials found at https://doi.org/10.1016/j.jval.2024.03.008.

Two time horizons w are considered: a short-term one corresponding to the median follow-up in the cohort under study and the "lifetime" one.

To identify the causal contrasts involving the potential outcomes in the definition of the ICER, the usual assumptions for causal inference must hold.[10] In our context, "consistency" refers to the principle that the time to the terminal event and the medical costs in a world where we intervene with treatment strategy P are the same in the real world where we observe the use of PCSK9-I. "Conditional exchangeability" assumes that the potential outcomes are independent of the allocation of the treatment, conditionally on the vector of observed covariates Z. Methods to achieve conditional exchangeability are discussed in the next section. Moreover, censoring times are assumed to be

Table 1. Summary of the protocol components of a target trial to study the cost-effectiveness of PCSK9-I in hypercholesterolemia.

Protocol component	Description of the target trial	How was the protocol element emulated using observational EHR data?	Challenges and potential sources of bias	Mitigation strategies to overcome challenges and potential bias
Eligibility criteria: Who will be included in the study?	Individuals eligible for the use of PCSK9-I to treat Hypercholesterolemia and living in the Trieste-Gorizia area of Italy according to the related reimbursement criteria established by AIFA. See the Supplemental Materials for the specific criteria.	Same as for the target trial with the exception that a single measurement of LDL above the threshold was considered valid. Required data for each person: age, LDL measurements, anamnesis, and family history of ASCVD and pharmacological treatment history.	Data might be insufficient to emulate the trial's eligibility criteria Leading to selection bias/ confounding.	The EHR data source used has complete coverage of the population of interest and contains all the available information necessary to define the eligibility criteria for PCSK9i (eg, laboratory values and treatment history). Expert opinion was used to translate the target trial criteria (eg, definition of ICD9 from inpatient data and their coupling with clinical diagnoses made by the cardiologists during specialist visits).
			The population selected for the study might include patients for whom there is no equipoise between treatment strategies leading to confounding bias.	According to the expert opinion, there were no reason to assume no equipoise for specific subgroups. During the IPTW diagnostics, we assessed the presence of patients for which there was no equipoise according to the distribution of the estimated propensity score, excluding them from the subsequent analyses.
			The population selected for the study might fail to include subgroups of interest for the cost-effectiveness analysis leading to nongeneralizable results or omission of relevant subgroup analyses.	The EHR data source is representative of the target population and subgroups of interest were identified using expert opinion.
Treatment strategies: What interventions will eligible persons receive?	Either standard LLT or LLT+ PCSK9-I	Same as for the target trial. Required data for each person: date of first prescription of PCSK9-I.	The definition of the intervention might differ from the intervention of interest.	It was possible to define precisely LLT and PCSK9-I using ATC codes, and they reflect the ones routinely used in clinical practice, according to expert opinion.
			The comparator strategy might not be defined with a sufficient level of detail.	It was possible to define precisely LLT using ATC codes, and they reflect the ones routinely used in clinical practice, according to expert opinion.

continued on next page

Table 1. Continued

Protocol component	Description of the target trial	How was the protocol element emulated using observational EHR data?	Challenges and potential sources of bias	Mitigation strategies to overcome challenges and potential bias
Time 0 and Follow-up period: During which period will eligible persons be followed in the study?	Time zero is the moment in which the subject starts being eligible for PCSK9-I. The recruitment period was from 1/7/2017 (entry of PCSK9-i in the Italian market) to 31/12/2020. The follow-up ends at the earliest of death loss at follow-up, or administrative end of the study (31/12/2021).	Time zero was assumed for individuals treated with PCSK9-I as the date of the first prescription and for the comparator group as the date at which the patients satisfied all the eligibility criteria. The follow-up was defined as in the target trial because complete follow-up data were available. Required data for each person: date of first prescription of PCSK9-I, date of eligibility to PCSK9-I, date of death, date of censoring.	The start of follow-up might predate the assessment of the eligibility criteria leading to selection bias. The time of treatment assignment might not be aligned with that of eligibility assessment and the start of follow-up leading to immortal time bias.	Time zero was chosen so that the start of the follow-up started when the assessment of the eligibility criteria had been made. The time zero chosen ensures that it minimizes time to treatment initiation because for PCSK9-I the date of treatment initiation should very closely follow the date of the first prescription, according to clinical guidelines and routine clinical practice.
Assignment procedures: How will eligible persons be assigned to the interventions?	Eligible participants will be randomly assigned to the two strategies and will be aware of the strategy to which they have been assigned.	Eligible persons will be assigned to the strategies with which their data are compatible.		
Outcomes: What outcomes in eligible persons will be compared among intervention groups?	Medical costs and LY on (1) a short time horizon (34 months) and (2) lifetime horizon taking into account possible repeated hospitalizations over time.	Same as for target trial (cost-effectiveness outcome). Required data for each person: dates of entry/exits from hospital with corresponding ICD9-CM and DRG code and date of death.		
Causal contrasts of interest: Which counterfactual contrasts will be estimated using the above data?	Intention-to-treat effect (effect of being assigned to treatment).	Observational analog of the Intention-to-treat effect.		
Statistical analysis: How will the counterfactual contrasts be estimated?	Intention-to-treat analysis via estimation of the ICER through multistate models and microsimulation.	Same as intention-to-treat analysis.	Confounding might exist after emulating the main components of the target trial, from both measured and unmeasured prognostic factors.	Inverse Probability of Treatment Weighting is used (together with diagnostics to assess the achievement of balance between the treatment groups) to eliminate confounding due to measured confounders. Sensitivity analyses based on the E-Value method are used to address the impact of possible unmeasured residual confounding in the cost-effectiveness results.

AIFA indicates Italian Medicines Agency; ATC, anatomical therapeutic classification; DRG, diagnosis related group; EHR, electronic health records; ICER, incremental cost-effectiveness ratio; LDL, low-density lipoprotein; LLT, lipid-lowering therapy; LY, life years; PCSK9-I, proprotein convertase subtilisin-kexin type 9- inhibitors.

conditionally independent of all potential event times. Finally, to satisfy "positivity," for each vector of covariates Z, the probability of being treated with PCSK9-I must be greater than 0.

Adjustment by Inverse Probability of Treatment Weighting

To achieve conditional exchangeability, we consider Inverse Probability of Treatment Weights (IPTW).[13,14] A multivariable gradient boosting classifier as implemented in the *twang* R package[15] is used to estimate the weights in terms of possible measured confounders: demographics, Charlson Comorbidity index, past atherosclerotic cardiovascular disease, diabetes with target organ damage or a risk factor (smoking, obesity, and hypertension), the history of treatment with statins (duration and adherence, measured as the proportion of days covered[16,17] by treatment), and the eligibility date. The IPTW weights used to obtain the identifiability of the quantity in Eq. (1) include all the above cited confounders, whereas for the quantity in Eq. (2) the covariates used to define the eligibility subgroups are excluded. When implementing the methods outlined in the subsequent sections, it is consistently assumed that the data set utilized has been weighted using IPTW.

Nonmodel-based Approach

It involves estimating the ICER nonparametrically by estimating the LY for each treatment group using the area under the Kaplan-Meier survival curve while considering the treatment group as a stratifying factor. Simultaneously, the mean medical costs are estimated using the Bang and Tsiatis estimator,[18] which takes into account censoring. It accomplishes this by appropriately weighting the sample mean medical costs in the two treatment groups. Confidence intervals are obtained through nonparametric bootstrap. It is important to note that, although this method does not rely on any modeling assumptions, only the short-term horizon can be considered because nonparametric estimates tend to become unstable when the number of individuals being observed is small.

Model-based Approach

An alternative approach consists of specifying a suitable statistical model to describe the risk of terminal events in the two treatments group and the medical cost-generating process. Individual-level health economic models are considered here for their flexibility among model-based methods. The steps involved in obtaining such model consists in (1) specify and fit a suitable disease model, (2) specify a suitable cost and health outcomes model, (3) run the decision (economic) model through the microsimulation, and (4) perform the decision analysis by estimating the ICER.

Disease Model

In the context of this application, the healthcare paths of individuals over time can be achieved by using a multistate model that depicts the potential multiple hospitalizations an individual may experience until their death. According to previous studies,[19] the set of discrete mutually exclusive states considered are "out-of-hospital," "in-hospital for acute coronary syndrome," "in-hospital for ischemic stroke," "in-hospital for periphery artery disease," "in-hospital for other cardiovascular causes," "in-hospital for noncardiovascular causes," and "death." The model is further defined by the transition intensities, $q_{rs}(t)$, which represent the instantaneous probability of moving from one generic state r to another generic state, s, conditionally on being still alive. The possible states and permitted transitions are illustrated in Fig. 1.

Under the simplest model, we assume that the transition intensities depend solely on the time since entry into the study and the treatment indicator. In such a model, there is no dependence of the transition intensities on the "history" of the process up to that specific time, ie, the previous states visited by the individual and the time spent in each of them. Essentially, the process is considered Markov. Given the complex nature of the process involving subjects' interactions with the healthcare system, in this study, we explore models capable of addressing potential violations of the Markov assumption. One approach considers the "clock-reset" time scale (see, eg, Putter et al.[20]) in which time returns to 0 at every transition. This enables us to model the hazard based on the timescale u, which represents the time since entry into the current state. To fit the model using the available data, the following cause-specific hazard models are used for the transition intensities, conditional on the treatment indicator:

$$q_{rs}(u|P=p) = q_{rs}^{0}(u)\exp\{p\beta\}$$

in which $q_{rs}^{0}(u)$ is the baseline transition hazard, p is the covariate for the treatment indicator, and β is its corresponding coefficient. $q_{rs}^{0}(u)$ is assumed to be parametric, but it is modeled via natural cubic splines to accommodate different shapes for hazard according to the Royston-Parmar flexible parametric model.[21] This class of models was fitted using the R package *flexsurv*.[22]

To introduce further dependence of the process on its history, both time-dependent covariates (eg, the number of previous hospitalizations) and a frailty model are considered. The frailty model considers the correlation between potential multiple transitions of the same type for the same individual by incorporating individual-specific random quantities known as frailties.

For model selection, eg, selection of number of degrees of freedom of the baseline transition hazard, Akaike Information Criteria, and Bayesian Information Criteria are used. Moreover, the overall goodness of fit of the models for the transition hazards is verified by comparing the predicted values of the cumulative hazard obtained from the models with the nonparametric estimates.

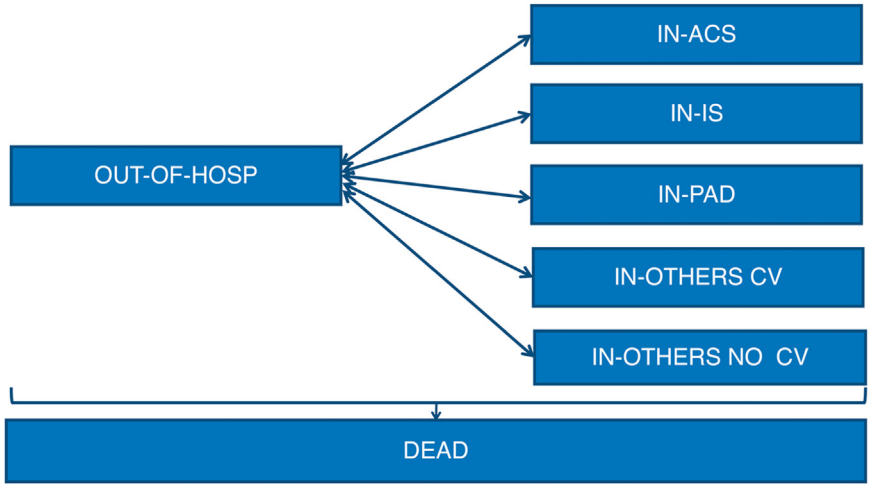
Finally, for the subgroup analysis, the previous model was modified by adding X as additional covariate.

Cost Model and Health Outcomes Model

The cost model, using Euros as currency, is formulated based on the regulations of the Italian public healthcare reimbursement system. In line with previous studies[19,23] and because all patients in this analysis were above retirement age, only direct costs associated with medication and hospitalizations were considered. Regarding the hospitalizations, in Italy, each diagnosis related group (DRG) code has a predetermined cost if the hospitalization duration is below a certain threshold. If the hospitalization exceeds that threshold, a daily cost is applied. In our model, we assume that when an individual is admitted to the hospital with a specific DRG code, the fixed cost is assigned, and additional costs based on the length of the simulated hospital stay are attributed. It is worth noting that multiple DRG codes are possible for each in-hospital state; therefore, we use a state-specific multinomial probability distribution to determine the probabilities of different DRG codes, which are estimated from the available data (see Supplementary Materials and Appendix Table 1 found at https://doi.org/10.1016/j.jval.2024.03.008). The average daily drug cost for the two treatment groups is derived from the Public Drug Distribution System and complete adherence is assumed for both groups for the entire time horizon.

In the main analysis, no adjustment for quality of life is incorporated; therefore, there is no utility model to be defined.

Figure 1. Structure of the multistate disease model. Possible states of the multistate disease model are out-of-hospital (OUT-OF-HOSP), in-hospital for acute coronary syndrome (IN-ACS), in-hospital for ischemic stroke (IN-IS), in-hospital for periphery artery disease (IN-PAD), in-hospital for other cardiovascular causes (IN-OTHERS CV), in-hospital for non-cv causes (IN-OTHERS NO CV), and death.



However, a sensitivity analysis using QALY instead of LY is performed. The utility model used is reported in Appendix Table 2 in Supplemental Materials found at https://doi.org/10.1016/j.jval.2024.03.008.

Finally, both costs and health outcomes are discounted at an annual rate of 3%.[24]

Decision Model Through Microsimulation and Decision Analysis

In essence, microsimulation involves simulating the life trajectories of individuals based on a specified health economic model using a random-number generator over the given time horizon *w*. Continuous microsimulation is used here because it does not require specification of model cycles and runs considerably faster.[5] Conceptually, microsimulation can also be viewed as an instrument to replicate the target trial based on the specified protocol.

To obtain confidence intervals, probability sensitivity analysis (PSA)[25] based on parametric bootstrap can be applied within the microsimulation framework. In standard microsimulation, individuals' paths are simulated based on the pointwise Maximum Likelihood estimate of the parameters that define the transition hazards. With PSA, the parameters are assumed to follow a multivariate normal distribution, according to the asymptotic behavior of the Maximum Likelihood Estimator. Therefore, in microsimulation with PSA, we first generate a random sample of *B* values for the parameter vector. Then, for each drawn parameter vector, we conduct a microsimulation with a sample of *N* individuals for each treatment strategy.

The microsimulation is performed using the *hesim*[5] R package with $N = 1000$ individuals for each of the 500 PSA samples and each treatment strategy (1 000 000 in total). Convergence diagnostics are reported in Appendix Fig. 1 in Supplemental Materials found at https://doi.org/10.1016/j.jval.2024.03.008.

The required estimates to calculate the ICER under each treatment strategy scenario, over the horizon *w*, are computed by averaging the total health outcomes and total costs across the simulated patients for each sample $b = 1, \ldots, B$.

Finally, the marginal and conditional ICER (along with their corresponding 95% confidence intervals) are calculated as the mean (2.5% and 97.75% quantiles) of the corresponding distribution derived from the *B* bootstrap samples.

Sensitivity Analyses

Different sensitivity analyses are carried out to assess the robustness and generalizability of the results. The first regards the extrapolation beyond the maximum follow-up observed in the data (sensitivity A). First, an independent historical cohort of subjects has been extracted ad hoc from the health electronic health records database with a follow-up compatible with the duration of the lifetime microsimulation. Transition hazards are estimated using this data set, and they were subsequently incorporated in the decision model as baseline transition hazards, after having them opportunely recalibrated on the study cohort. In a second sensitivity analysis, a different scenario considering that a portion of individuals are not adherent to the treatment is considered (sensitivity B). In addition, we used the E-Value methodology[26] (using the R package *Evalue*[27]), to quantify the degree to which the cost-effectiveness results may be affected by different unmeasured confounders scenarios when estimating the treatment effects using observational data (sensitivity C). The E-value was selected because of its lack of dependence on specific assumptions and its flexibility,[28] making it suitable for integration into the methodology used for the CE analysis. Specifically, we consider three microsimulations with a less protective treatment effect for all-cause death compared with the main analysis. Finally, sensitivity analysis D incorporates utilities (Appendix Table 2 in Supplemental Materials found at https://doi.org/10.1016/j.jval.2024.03.008) to estimate QALY.

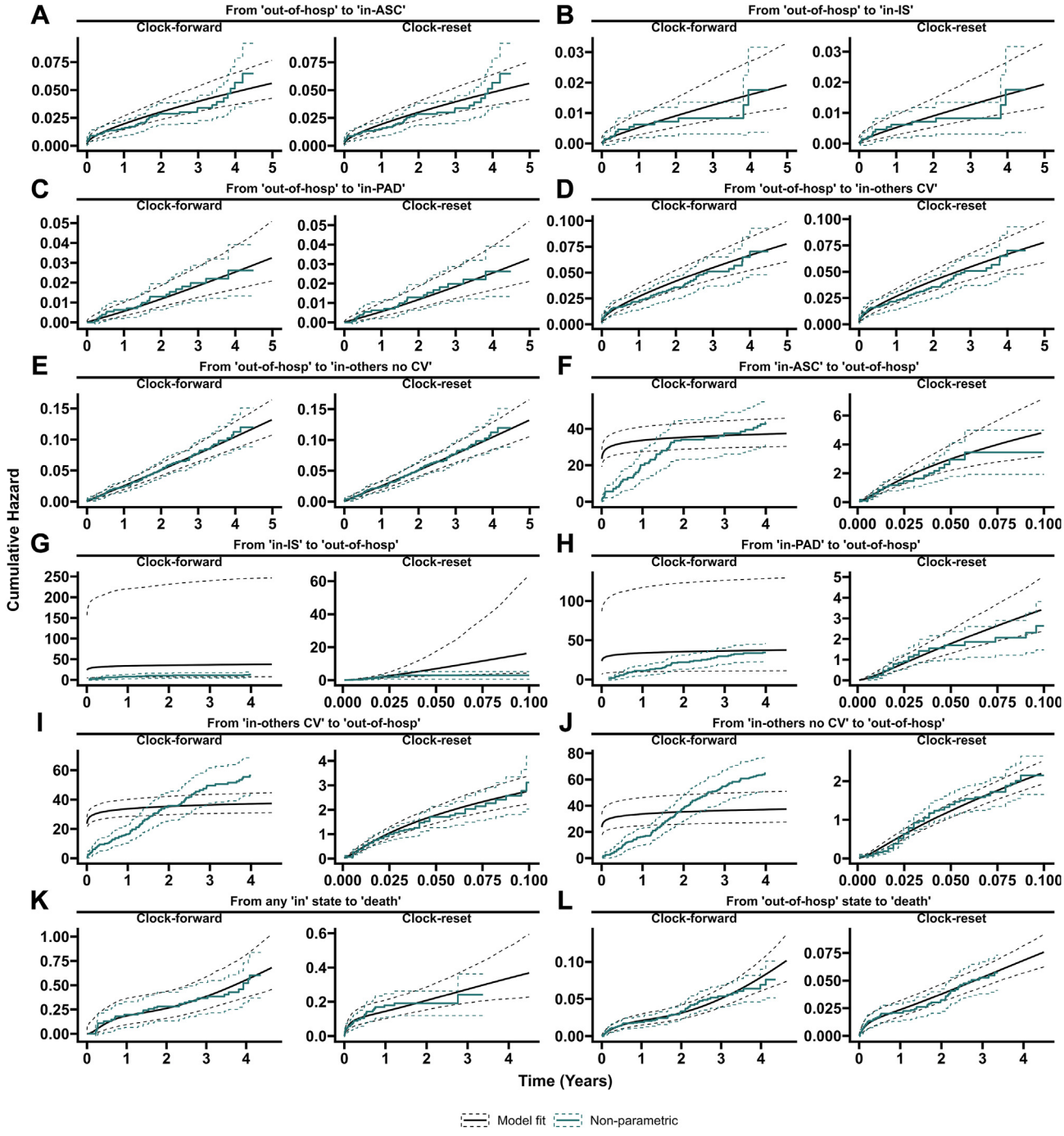
The Consolidated Health Economic Evaluation Reporting Standards reporting guideline checklist[29] is reported in the Supplementary Materials found at https://doi.org/10.1016/j.jval.2024.03.008.

Results

Study Cohort

We extracted data related to 96 886 subjects with at least 1 measure of LDL available in the enrollment period (from 1/7/2017 to 31/12/2020). Among these, at least 1 of the eligibility criteria

Figure 2. Goodness of fit of multistate disease model using "clock-forward" vs "clock-reset" timescale. For each type of transition, the predicted baseline cumulative transition hazards obtained from either the Markov ("clock-forward") or Semi-Markov ("clock-reset") model with have been compared with the nonparametric estimates (green curves). Dashed lines correspond to 95% CI. Considering the Semi-Markov model, all transition-hazard models in (A) to (L) show a satisfactory goodness of fit because the 95% CI of the model fit overlaps the corresponding nonparametric estimate. On the other hand, the Markov model shows lack of goodness-of-fit, especially with regard to the transitions in (F) to (J).



occurred during the observation period for 1976 subjects (2%). Among them, 161 (8%) were prescribed to PCSK9-I. The median follow-up time was 34 months.

Subjects on LLT+PCSK9-I were slightly younger, prevalently males, with more severe CV conditions and a higher rate of statin treatment with respect to the subjects belonging to the LLT group (Appendix Table 3 in Supplemental Materials found at https://doi.org/10.1016/j.jval.2024.03.008). Patients nontreated with PCSK-I showed higher prevalence of comorbidities, such as diabetes, chronic obstructive pulmonary disease, and renal diseases.

Table 2. Effect of PCSK9-I+LLT estimated on transition hazards through the disease model.

Transition type		HR	95% CI
Toward hospital	PCSK9-I+LLT vs LLT first hospitalization	0.79	0.63; 0.99
	PCSK9-I+LLT vs LLT 2+ vs 1 hospitalization	0.91	0.62; 1.34
Toward out-of-hospital	PCSK9-I+LLT vs LLT 2+ vs 1 hospitalization	1.21	0.93; 1.56
	PCSK9-I+LLT vs LLT 2+ vs 1 hospitalization	0.87	0.58; 1.31
Toward death	PCSK9-I+LLT vs LLT	0.14	0.07; 0.27

CI indicates confidence interval; HR, hazard ratio; LLT, lipid-lowering therapy; PCSK9-I, proprotein convertase subtilisin-kexin type 9- inhibitors.

Diagnostics of the IPTW procedure are shown in Appendix Table 4 in Supplemental Materials found at https://doi.org/10.1016/j.jval.2024.03.008. A satisfactory balance has been achieved for all the covariates. Individuals with estimated propensity scores indicating potential violations of the positivity assumption were excluded from the diagnostics and subsequent analysis (26% of the study cohort).

Disease Model, Cost, and Utility Model

The comparison between the "time-reset" scale and the "time-forward" (Markov model) is depicted in Fig. 2, confirming the relevance of considering the former time scale in this context to accurately capture the transition intensities from in-hospital states to the out-of-hospital state (Fig. 2, from [F] to [J]). Regarding the dependence on the past history of the process, a time-varying covariate that distinguishes the first hospitalization from subsequent ones exhibited the best goodness of fit based on the Akaike Information Criteria; therefore, it was chosen among models with different definitions of the time-dependent variable and the frailty model.

The final models incorporated distinct baseline hazards for each transition, but the effect of PCSK9-I treatment was assumed to be consistent across different causes of hospitalization and between death occurring in and out of the hospital (Table 2). We made this assumption because considering a more complex specification of the model did not demonstrate a significant improvement in terms of goodness of fit.

A significant strong protective effect of PCSK9-I on all-cause death (hazard ratio [HR] = 0.14, 95% CI 0.07-0.27) was observed, and a significant protective effect of PCSK9-I was detected only for the transition toward the first hospitalization (HR = 0.79, 95% CI 0.63-0.99).

All the disease models' parameters are reported in Appendix Table 5 (main analysis) and in Appendix Table 6 (subgroup analysis) in Supplemental Materials found at https://doi.org/10.1016/j.jval.2024.03.008.

CE Results

The short-term ICER at 34 months obtained with the model-based and nonmodel-based approaches were not statistically different and showed a minimum willingness to pay of Euro/LY >200 000 (Appendix Fig. 2 in Supplemental Materials found at https://doi.org/10.1016/j.jval.2024.03.008). The results of the lifetime analysis model are reported in Table 3. According to these results, an ICER of 29 540 (95% CI: 23 773-38 949) Euro/LY was obtained (Fig. 3A).

The subgroup analysis showed that patients with diabetes with organ damage and/or a risk factor have a lower minimum willingness to pay (Fig. 3B, Appendix Table 7 in Supplemental Materials found at https://doi.org/10.1016/j.jval.2024.03.008).

Results of the Sensitivity Analyses

Sensitivity analysis A leads to results consistent with the ones obtained through the main lifetime decision model (Appendix Fig. 3A in Supplemental Materials found at https://doi.org/10.1016/j.jval.2024.03.008), and the long-term mortality rates of the historical cohort are overlapping with the ones estimated from the disease model for the nontreated group (Appendix Fig. 3B in Supplemental Materials found at https://doi.org/10.1016/j.jval.2024.03.008).

In sensitivity analysis B, considering an estimated fraction of 7% of nonadherent individuals to PCSK9-I, as reported by Arca et al.,[30] an ICER of 29 905 (95% CI: 23 982-38 604) Euro/LY was observed (Appendix Fig. 4 in Supplemental Materials found at https://doi.org/10.1016/j.jval.2024.03.008).

Assuming a treatment effect for all-cause death more similar to the one observed in RCTs, the ICER reached 58 000 Euro/LY (Appendix Fig. 5 in Supplemental Materials found at https://doi.org/10.1016/j.jval.2024.03.008).

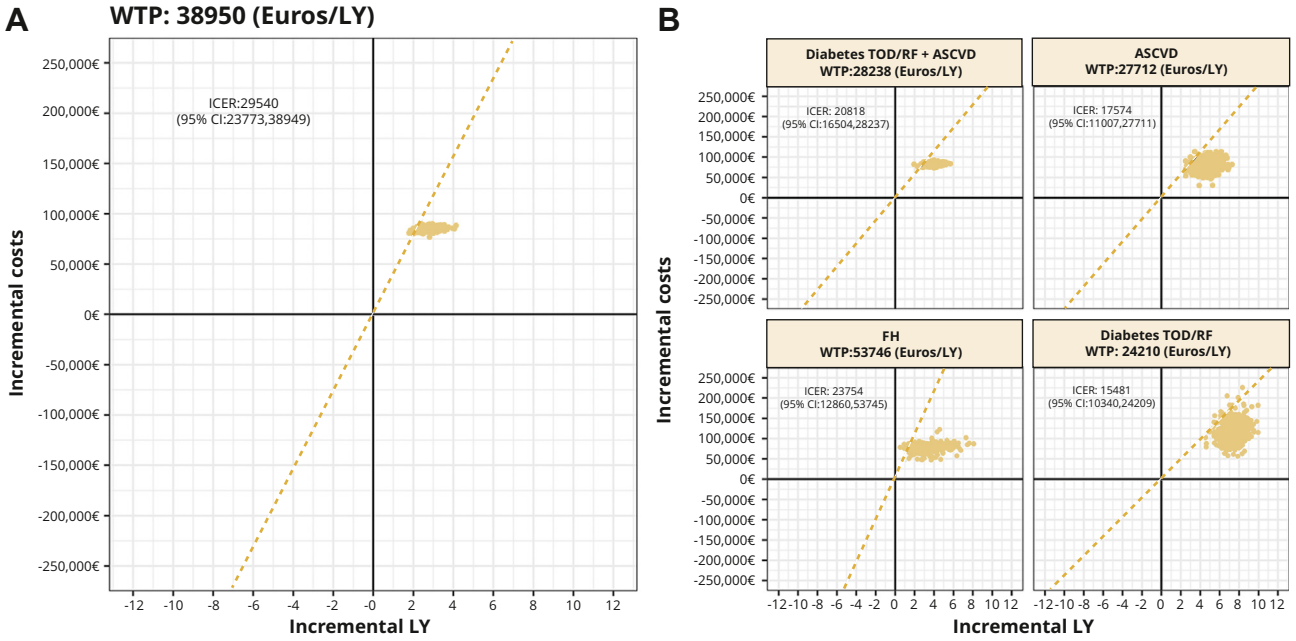
In sensitivity analysis D, an ICER of 29 292 (95% CI: 23 550-37 888) Euro/QALY was estimated (Appendix Fig. 6 in Supplemental Materials found at https://doi.org/10.1016/j.jval.2024.03.008).

Table 3. Results of the microsimulation economic model.

Quantity	LLT (95% CI)	PCSK9-I+LLT (95% CI)
Mean utility (years)	17.13 (16.45, 17.75)	20.02 (19.56, 20.32)
Mean costs: drugs (Euros)	1850 (1776, 1917)	88 655 (86 611, 89 986)
Mean costs: hospitalizations length of stay below threshold (Euros)	6228 (3806, 11 577)	5510 (3241, 10 217)
Mean costs: hospitalizations extra days (Euros)	2704 (1920, 3965)	1954 (1229, 2906)

CI indicates confidence interval; HR, hazard ratio; LLT, lipid-lowering therapy; PCSK9-I, proprotein convertase subtilisin-kexin type 9- inhibitors.

Figure 3. Lifetime cost-effectiveness results. On the left, the cost-effectiveness plane and ICER with 95% CI is displayed in the whole cohort (A). On the right, the cost-effectiveness planes and corresponding ICER with 95% CI within each subgroup of interest are displayed (B). The dashed lines on the cost-effectiveness planes represent the minimum willingness to pay in Euros per LY gained for the treatment to be considered cost-effective at 95% confidence level.



Discussion

CE analysis using RWD is a promising yet challenging field. In our study, we combined target trial emulation with flexible statistical methods. In chronic illnesses, such as cardiovascular conditions, assessing lifetime CE is crucial. Our application on PCSK9-I revealed substantial differences in CE between short and long-term perspectives.

To evaluate long-term CE, decision models based on RWD become essential because they encompass limitations common to RCTs and observational studies related to a limited follow-up period, when the focus is on drugs recently approved. Thus, selecting an appropriate decision model and assessing its goodness of fit using available observational data are crucial steps. Although nonparametric methods have limitations in conducting comprehensive scenario analyses, they can still provide valuable insights. By keeping the same time horizon, the results obtained from the nonparametric approach should be consistent with those derived from the decision model, if the disease and cost models are correctly specified. Indeed, this was the case for our decision model. In this study, we were able to achieve this by using a flexible parametric multistate model combined with a microsimulation model. Although cohort models are suitable for obtaining marginal estimates of CE, microsimulation can simulate individual life-course trajectories between health states, allowing for more personalized analyses. Moreover, individual-level models naturally capture the accumulation of costs in real healthcare systems.

Using this approach, we could overcome the limitations of Markov assumptions and incorporate the history of hospitalizations. This significantly improved the goodness of fit. The inadequacy of Markov models for modeling healthcare paths is a well-established topic in biostatistics literature.[31] Nevertheless, decision models based on the Markov assumption are standard methods in cost-effectiveness analyses for chronic illnesses.

In addition to the disease model's goodness of fit, it is also essential to assess the convergence of the microsimulation and perform different sensitivity analyses. Lifetime decision models involve extrapolation. In this article, we have tested the robustness of such extrapolation using data from a historical cohort extracted from our EHR database. We also considered a scenario in which not all individuals prescribed to the treatment adhere to it, according to the observed nonadherence rate in Italy for PCSK9-I.[30] Finally, the treatment effect of the drug on the risk of death estimated in our study was much higher than the one observed in the RCTs.[6-8] This may be partly due to the higher cardiovascular risk of our cohort of subject. As it has been shown in a RCTs subgroup analysis,[6] patients at higher risk seem to benefit the most from PCSK9-I. However, unmeasured confounding could also not be ruled out given the observational nature of the study. Therefore, in another sensitivity analysis, we assessed how the estimate for the ICER changed according to different scenarios of unmeasured confounding resulting in a treatment effect of PCSK9-I on death closer to the one reported in a meta-analysis.[32]

To the best of our knowledge, this study provides the first CE analysis on PCSK9-I for the Italian healthcare system using RWD. According to our results, the ICER about 30 000 Euro per health outcome gained, both considering the LY and QALY. However, in case of a much less protective treatment effect on death, the ICER reaches 58 000 Euro per LY gained. Results from other investigations on the CE of PCSK9-I are heterogeneous, as are the health economic models used. However, some results are in line with the one obtained in this study.[19,23]

Conclusions

In conclusion, this work provides evidence on the CE of PCSK9-I using RWD. Furthermore, this study demonstrates the potential of

individual-level decision models for CE analysis using RWD. The framework of disease and cost models presented here can be extended to other applications or healthcare systems. Moreover, it could be possible to consider scenarios in which it is of interest to examine CE based on more detailed subject profiles, allowing for personalized analyses.

Author Disclosures

Author disclosure forms can be accessed below in the Supplemental Material section.

Supplemental Material

Supplementary data associated with this article can be found in the online version at https://doi.org/10.1016/j.jval.2024.03.008.

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