Mapping Disease-specific Patient-reported Outcome Measures (PROMs) to EQ-5D Utility Scores: A Systematic Review

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INTRODUCTION

Preference-based general utility scores are needed to calculate QALYs in cost-utility studies. However, many clinical trials report effectiveness in terms of PROMs, hence mapping techniques are often needed.

OBJECTIVE

To identify existing techniques to map disease-specific PROMs to preference-based general utility values

METHOD

EconLit, Embase, PubMed, Scopus were searched from database inception to April 28, 2025 for mapping studies between disease-specific PROMs and utility based on EQ-5D. Search results were reviewed by two blinded independent reviewers.

RESULTS

Of the 780 abstracts identified, 365 duplicates were removed. The remaining 415 abstracts were independently screened by two blinded reviewers, leading to 143 full-text reviews and 132 studies included in the final analysis. Interest in mapping between PROMs and utility measures spans multiple clinical areas, including general cancer (n = 14 studies), knee osteoarthritis (n = 7) and breast cancer (n=7). Frequency counts by disease area and PROM are reported in the Supplementary Appendix.

Two principal approaches have been developed for mapping from disease-specific PROMs to EQ-5D–based utilities: **direct mapping**, which models utilities obtained from country-specific EQ-5D tariffs, and **response mapping**, which models the probability of responses on each EQ-5D dimension and subsequently derives utilities.

Among selected studies, **direct mapping dominated** (n = 128), with models ranging from traditional linear and generalized linear frameworks to more sophisticated limited dependent variable models, bounded-outcome regressions, multi-part models, and a smaller number of machine-learning methods.

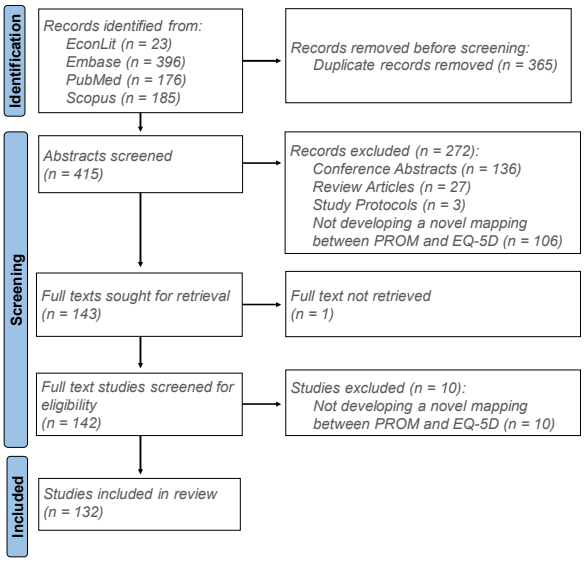

Figure 1: PRISMA flow diagram

Approach	Method Class	Example models
Direct Mapping (n = 128)	Classic Linear and Generalized Linear models (n = 88)	OLS, GLM, piecewise OLS, Spline models
	Limited Dependent Variable models (n = 48)	Tobit regression, CLAD, ALDVMM
	Bounded Outcome / Fractional Response Models (n = 12)	Beta Regression, Fractional logistic regression
	Multi-part Models (n = 25)	Two-part OLS, Two-part GLM, Two-part Beta regression, Two-part Tobit regression, Mixture regression models
	Machine-learning methods (n = 2)	Random forest, LASSO, Gradient Boosted Trees
	Missing data framework (n = 1)	Frequentist/Bayesian multiple imputation
	Rank/Quantile based methods (n = 3)	Mean rank method, Quantile regression, Logistic quantile regression
	Hierarchical & Correlated-Data Models (n = 12)	Multilevel analysis, mixed models, GEE
	Robust estimators (n = 6)	MM-estimator
	Non-Linear & Flexible Regression Frameworks (n = 3)	Multivariable Fractional Polynomials, Generalized Additive Model
Response Mapping (n = 36)	Parametric, independent models for each dimension (n = 17)	Ordinal logistic regression, Ordered probit, Generalized ordered probit
	Parametric, multivariate jointed models of all dimensions (n = 16)	Multivariate ordered probit, Multinomial Logistic regression, Seemingly unrelated ordered probit model
	Regularized models (n = 1)	Penalized Ordinal Regression
	Tree-based models (n = 2)	Gradient Boosted Trees, Classification and Regression Trees, Ordinal Random Forest
	Bayesian network models (n = 1)	Bayesian networks, Class-Bridge MBCs, Markov Blanket MBCs, Indipendent Markov blankets algorithm

Table 1: Cross-walking methods used in literature by approach type and method class. n is the number of studies using a given approach or class.
Abbreviations: ALDVMM: Adjusted Limited Dependent Variable Mixture Model; CLAD: Censored Least Absolute Deviation; GEE: Generalized Estimating Equations; GLM: Generalized Linear Model; LASSO: Least Absolute Shrinkage and Selection Operator; MBC: Multidimensional Bayesian network classifer; OLS: Ordinary Least Square.

Response mapping may offer higher transferability across populations and value sets, as it models EQ-5D dimensions directly, and it facilitates the construction of valid confidence intervals by allowing uncertainty to propagate naturally through the predicted response probabilities. Yet, **response mapping methods were less common** (n = 36).
Additionally, only a minority of these - those employing multivariate or network structures - explicitly accounted for the correlation among EQ-5D dimensions, highlighting an area of ongoing methodological limitation and opportunity for further development.

Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were the most common metrics for model selection. Nearly all studies validated mapping results either on a new set of data or through k-fold cross-validation, using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) as the primary metrics.

CONCLUSIONS

Direct mapping remains the predominant approach for deriving EQ-5D utilities from disease-specific PROMs, though response mapping offers conceptual advantages in transferability and inference. The limited treatment of correlations among EQ-5D dimensions highlights an important methodological gap. Future research should focus on multivariate and probabilistic frameworks that better capture joint outcome structures while maintaining practical usability.

REFERENCES

References for all studies included in full-text review are listed in the Supplementary Appendix

CONTACT INFORMATION

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