

Development of Mapping Algorithms from HAQ-DI and SF-36v2 to EQ-5D-5L utility score in Korean Patients with Gout

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Abstract

Purpose.

This study aimed to map health-related quality of life (HRQoL) score into utility score which can be used in cost-effectiveness analysis in Korean gout patients. The research team used HAQ-DI and SF-36v2 to predict EQ-5D-5L utility scores for gout patients.

Methods.

Adults aged 19–75 with gout from 13 Korean hospitals completed the HAQ-DI, SF-36v2, and EQ-5D-5L at two visits at least one month apart. Utility scores were derived using the Korean EQ-5D-5L value set. Nine regression methods (OLS, Tobit, CLAD, GLM, two-part, beta-mixture, ALDVMM, multinomial logistic, multivariate probit) were applied, with and without age and sex. Models were validated on second-visit data and assessed by MAE, ICC, and absolute-error proportions.

Results.

The mean EQ-5D-5L utility scores were 0.9114 in first and 0.9281 in second visit. The two-part model was recommended to predict utility scores from HAQ-DI and SF-36v2 (HAQ-DI: RMSE = 0.0863, MAE = 0.0745, AIC = 357.1480/-270.7789, BIC = 364.6212/-262.0409, AE > 0.05(%) = 87.2549, AE > 0.1(%) = 15.6863, ICC = 0.5235) / SF-36v2: RMSE = 0.0877, MAE = 0.0668, AIC = 331.5214/-261.4394, BIC = 342.6327/-249.9386, AE > 0.05(%) = 46.5347, AE > 0.1(%) = 15.8416, ICC = 0.5389 for the internal validation set). The model mapping from HAQ-DI included only HAQ-DI score as the predicted variable, and the model mapping from SF-36v2 included two summary scores (PCS, MCS) as the predicted variables showing the best performance.

Conclusion.

This study offers validated mapping algorithms for mapping HAQ-DI and SF-36v2 scores into EQ-5D-5L utility scores in Korean patients with gout, supporting evidence generation for clinical and healthcare decision-making.

Introduction

Gout is the most common form of inflammatory arthritis in adults, and its burden has steadily risen globally [1]. The disease arises from the deposition of monosodium urate crystals in joints and soft tissues following sustained hyperuricemia [1]. It manifests clinically as recurrent acute flares, chronic arthropathy. In advanced stages, tophus formation and joint damage occurs. The reported number of gout patients in 2020 was 55.8 million globally and has steadily increased since 1990 [2]. The disease predominantly affects men, with a male-to-female ratio of approximately 3.26 [2]. In Korea, 766,469 patients were reported in 2015 and about 3 times of male participants comparing with female were reported [3]. Its rising incidence has been attributed to the aged population with the increasing prevalence of obesity, metabolic syndrome, and chronic kidney disease [2]. Gout also carries a substantial economic burden [2, 4]. Direct medical costs for gout have been estimated at, main cause belongs to emergency and outpatient visits for acute flares and by the management of associated comorbidities [4].

Gout imposes a burden on health-related quality of life (HRQoL) beyond the acute flare [5]. Patients report reduced psychological well-being by impaired physical function, persistent pain, restricted daily and occupational activity [6]. These comprehensive inconveniences lead to decrease in quantitatively evaluated HRQoL. The Health Assessment Questionnaire Disability Index (HAQ-DI) is widely used in inflammatory arthritis to quantify functional disability in daily activities, and the Short Form-36 Health Survey version 2 (SF-36v2) is among the most widely applied generic measures of HRQoL. Both instruments have been translated into Korean and have demonstrated acceptable measurement properties in Korean populations [7, 8]. Because both instruments are non-preference-based measures, neither can be used directly to analyze the health state utility scores required for economic evaluation.

Economic evaluation of health technologies increasingly relies on cost-effectiveness analysis expressed in terms of quality-adjusted life years (QALYs). It requires health state utility scores which anchored at 1 for full health and 0 for death to measure QALYs. Because direct evaluation of preferences using standard methods is complex in cases of disease specific instruments, pharmacoeconomic guidelines recommend the use of validated multi-attribute utility instruments to obtain values indirectly [9]. Among these instruments, the EQ-5D is the most widely applied internationally, and it is the instrument specified for use in pharmacoeconomic evaluation in Korea [9, 10]. Utility scores are further dependent on the value set applied, and a Korean value set for the EQ-5D-5L has been established [10]. Using the Korean value set, it is intended to inform Korean reimbursement decisions should be generated using Korean preference weights.

Mapping is an established method for deriving utility scores when a preference-based measure has not been administered. Two approaches are recognized, direct and indirect mapping. While direct mapping mount the utility score of the target instrument on the scores of the source instrument, indirect mapping organize the probability of each response level within each dimension of the target instrument and then applies the relevant value set to the predicted health state probabilities. The process of mapping is addressed by the ISPOR Good Practices for Outcomes Research Task Force report [11]. Their reporting was addressed by MAPS statement [12]. The predictive performance of any mapping algorithm depends on the degree of conceptual overlap between the source and target instruments, and algorithms are specific to the population, the instrument version, and the value set which they were estimated. Consequently, mapping models developed in one setting might not be applied to another.

Despite availability of mapping algorithms for a range of chronic conditions, no algorithm currently exists to derive EQ-5D-5L utility scores from the HAQ-DI or the SF-36v2 in patients with gout. Previous mapping work involving the HAQ-DI has been conducted predominantly in rheumatoid arthritis, and the transferability of these algorithms to gout is uncertain because the two conditions differ in symptom pattern, and comorbidity profile [13]. In the Korean setting, Kim et al. derived algorithms converting SF-36 scores to the EQ-5D index using the Korean value set, but that work targeted the three-level version of the EQ-5D and drew on general population, diabetes, stroke, and colon cancer samples rather than a gout-specific population [14]. The absence of a gout-specific, EQ-5D-5L based, Korean algorithm limits the ability to conduct cost-effectiveness analyses of gout treatments using existing HAQ-DI and SF-36v2 datasets. The objective of this study was therefore to develop and validate mapping algorithms predicting EQ-5D-5L utility scores, derived using the Korean value set, from HAQ-DI and SF-36v2 scores in Korean patients with gout.

Methods

Study population and data collection

Data was obtained from a multicenter, longitudinal, observational study of patients with gout conducted at 13 hospitals in Korea between April 2025 and March 2026. Eligible patients were adults aged 19 years to 75 years old with a diagnosis of gout, who were able to read and complete the study questionnaires independently and who provided written informed consent.

Sociodemographic characteristics and clinical information, including the number of gout flares and the number of occurrences on limited joints preceding six months, were recorded at enrollment. The HAQ-DI, SF-36v2, and EQ-5D-5L were administered at first and second visits, at least one-month intervals. Questionnaires were self-completed with printed paper.

The study protocol was approved by the Institutional Review Board of Ewha Womans University (IRB approval no. ewha-202504-0032-01). All participants provided written informed consent.

Source measures

- HAQ-DI

The HAQ-DI is a self-administered measure of functional disability with 20 items across eight domains: dressing and grooming, arising, eating, walking, hygiene, reach, grip, and common daily activities. Each item is scored from 0 (without any difficulty) to 3 (unable to do), and category scores are adjusted for the use of aids, devices, or assistance from another person [15, 16]. The overall HAQ-DI score is the mean of the eight category scores and ranged from 0 to 3, with higher scores indicating greater functional disability. The Korean version of the HAQ-DI has demonstrated acceptable reliability and validity [7].

- SF-36v2

The SF-36v2 is a generic profile measure of HRQoL with 36 items that generate eight domain scores, including physical functioning (PF), role-physical (RP), bodily pain (BP), general health (GH), vitality (VT), social functioning (SF), role-emotional (RE), and mental health (MH), and two summary scores, the physical component summary (PCS) and the mental component summary (MCS). Scores were calculated using norm-based scoring, standardized to a mean of 50 and a standard deviation of 10 using Korean general population norms [8]. The higher scores indicated better health status. The Korean version of the SF-36v2 has demonstrated acceptable measurement properties in Korean populations [8].

- Target measures: EQ-5D-5L

The EQ-5D-5L is a general preference-based measure with EQ-VAS and a descriptive system comprised of five dimensions including mobility, self-care, usual activities, pain/discomfort, and anxiety/depression. Each dimension requires five response levels ranging from no problems to extreme problems, defining 3,125 unique health states. Responses were converted into a single utility index using the Korean EQ-5D-5L value set [10], which ranges from – 0.066 for the worst state (55555) to 1 for full health (11111). The meaning of utility score was presented as 1 for full health, 0 for death, and negative values for states considered worse than death [17].

Model specification

The general form of the models can be expressed as:

$$Eq-5D-5L = f(HAQ-DI, SF-36v2, age, sex)$$

where f is the regression method applied. On this basis following predictor sets were specified:

1. HAQ-DI total score only
2. SF-36v2 two summary scores only
3. SF-36v2 eight domain scores only
4. Predictor set with age and sex

Age and sex were included as covariates, as ISPOR Good Practice recommendations for avoiding model misspecification and with evidence that both are associated with HRQoL in gout.

Regression methods

Ordinary least squares (OLS): OLS is the most frequently applied method in the mapping because of its computational simplicity. It relies on the assumptions of normally distributed residuals and constant variance, and it does not constrain predictions to the feasible range of the target instrument [18].

Tobit: The Tobit model addresses censoring of the dependent variable by assuming an underlying latent utility variable with a Gaussian distribution. It provides consistent parameter estimates by maximum likelihood. Because EQ-5D-5L utility scores can't exceed 1 and exhibit a ceiling, the Tobit model can be a proper model for mapping [19].

Censored least absolute deviation (CLAD): CLAD applies quantile regression to censored data and estimates the conditional median rather than the mean. It does not require a parametric distributional assumption for the error term, and is less sensitive to outliers and to the skewness characteristics of utility data [20].

Generalized linear model (GLM). GLM extends the linear model through a link function and a distributional family, accommodating non-linear relationships between predictors [20].

Two-part model: The two-part model was included to accommodate the observations at full health. In the first part, logistic regression was used to model the probability of reporting the 11111 health state. In the second part, GLM was used to model utility among observations not in full health. Predictions from the two parts were combined to yield the predicted utility value [21].

Beta-mixture: A beta-mixture model represents utility scores using a mixture of two or more beta distributions. This allows the model to accommodate skewness, multimodality, and the bounded nature of EQ-5D-5L utility value [22].

Multinomial logistic (MNL): The MNL model was applied as an indirect (response) mapping approach. Rather than modelling the utility value directly, a separate multinomial logistic regression was estimated for each of the five EQ-5D-5L dimensions, with the response level (1–5) as the dependent variable and the source instrument scores as predictors [23].

Adjusted limited dependent variable mixture model (ALDVMM): The ALDVMM is a mixture of adjusted normal distributions. It accounts for bounded discontinuous, and multimodal distributions including the gap between full health and the next feasible health state. The number of components in this study were 1, 2, and 3 [24].

Multivariate probit (MV-probit): An MV-probit model predicts multiple correlated health dimensions in EQ-5D-5L, while accounting for correlations between them. Predicted dimension responses are then combined to obtain the corresponding utility value [25].

Model validation

The development set comprised all observations with complete data at first visit, and the validation set comprised observations at second visit. Models estimated in the development set were applied to the validation set, and predicted values were compared with observed values to assess that algorithms had consistency.

In addition, internal validation was performed within the development set using 75/25 split random-sample validation. For the random-sample validation, 75% of observations were used for estimation and the remaining 25% for evaluation.

Model performance and model selection

Model performance was evaluated using several fit statistics: the mean absolute error (MAE), the root mean squared error (RMSE), intraclass correlation coefficient (ICC), and the proportions of estimation with absolute error (AE) over 0.05 and 0.1. Lower MAE, RMSE, and absolute error proportions and higher ICC indicated better performance. The Akaike information criterion (AIC) and Bayesian information criterion (BIC) were reported to assess goodness of fit for the estimation dataset.

In addition to the statistics, the observed and predicted distributions were compared with mean, standard deviation, minimum, maximum, and median.

All analyses were performed using R 4.5.2 and STATA 19.5 [26, 27].

Results

Sample characteristics and descriptive statistics

Total 412 patients were enrolled across 13 hospitals in South Korea. Whole 412 patients completed EQ-5D-5L questionnaires, but 403 and 401 patients completed HAQ-DI and SF-36v2 each on first visit. In second visit, 394 patients completed EQ-5D-5L, 384 completed HAQ-DI and 378 completed SF-36v2.

The characteristics of the patients were presented in Table 1. In first visit, the mean age was 51.61 (SD: 12.92) and 402 were male. They reported average 0.77 (SD: 1.33) on gout attacks and average 0.53 (SD: 0.82) on limited joints in the preceding six months. In second visit, the mean age was 51.75 (SD: 12.94) and 384 were male. They reported average 0.53 (SD: 1.09) on gout attacks and 0.38 (SD: 0.71) on limited joints in the preceding six months.

Table 1
Participants characteristics

	First		Second	
	N	%	N	%
Sex	402	97.57	384	97.46
Male	10	2.43	10	2.54
Female				
Age	17	4.13	16	4.06
30 <	63	15.29	60	15.23
30 ≤ < 40	102	24.76	95	24.11
40 ≤ < 50	94	22.82	92	23.35
50 ≤ < 60	100	24.27	96	24.37
60 ≤ < 70	36	8.74	35	8.88
70 ≥				
Weight (kg)	80.91	-	80.66	-
Mean, (SD, Min - Max)	(14.59, 34–158)		(14.18, 34–158)	
Height (cm)	171.67	-	171.58	-
Mean, (SD, Min - Max)	(6.92, 146–191.2)		(6.92, 146–191.2)	
BMI	27.36	-	27.31	-
Mean, (SD, Min - Max)	(4.13, 15.95–54.67)		(4.03, 15.95–54.67)	
Number of gout attacks	0.77	-	0.53	-
Mean, (SD, Min - Max)	(1.33, 0–5)		(1.09, 0–5)	
Number of limited joints	0.53	-	0.38	-
Mean, (SD, Min - Max)	(0.82, 0–3)		(0.71, 0–3)	

Instrument scores and distribution of utility scores

Descriptive statistics for all three instruments were presented in Table 2 and distribution of scores were presented in Fig. 1. The number of patients who reported full health by EQ-5D-5L was 231 (56.07%) in first visit and 242 (61.42%) in second visit.

Table 2
HRQoL instrument score

EQ-5D-5L	First	Second
Mean, (SD, Min - Max)	0.9114 (0.1175, 0.393-1.000)	0.9281 (0.1027, 0.340-1.000)
HAQ-DI	0.1335 (0.3444, 0-2.3750)	0.1104 (0.2898, 0-2.000)
Mean, (SD, Min - Max)		
SF-36v2 PCS	48.13 (8.59, 14.54–61.71)	49.44 (7.30, 23.34–62.35)
Mean, (SD, Min - Max)		
SF-36v2 MCS	51.05 (9.57, 2.86–72.80)	51.43 (9.29, 6.31–71.97)
Mean, (SD, Min - Max)		

Model performance

The performance evaluation on each model by development dataset was summarized in Table 3-a for the HAQ-DI and Table 3-b for the SF-36v2. The performance evaluation by internal validation dataset was summarized in Table 4-a and Table 4-b.

Table 3
a. Comparison of mapping model derived from development dataset – HAQ-DI to EQ-5D-5L

Model	RMSE	MAE	AE > 0.05 (%)	AE > 0.10 (%)
Basic model				
1compartment ALDVMM	0.1024	0.0820	94.8387	18.3871
2compartment ALDVMM	0.1023	0.0843	95.4839	19.3548
3compartment ALDVMM	0.1040	0.0864	96.1290	19.6774
Beta	0.1024	0.0845	92.9032	19.6774
CLAD	0.1146	0.0684	41.9355	34.8387
GLM	0.0986	0.0809	91.9355	16.1290
MM	0.2808	0.1286	44.5161	41.9355
MV-probit	0.1453	0.0864	43.2258	42.9032
OLS	0.0998	0.0818	92.2581	16.7742
Tobit	0.1213	0.0720	41.2903	38.3871
Two-part	0.0966	0.0778	91.2903	14.5161
Model with demographic covariates				
1compartment ALDVMM	0.1024	0.0820	95.1613	18.7097
2compartment ALDVMM	0.1031	0.0846	94.8387	18.7097
3compartment ALDVMM	0.1011	0.0839	96.1290	20.0000
Beta	0.1023	0.0845	93.2258	19.6774
CLAD	0.1255	0.0748	43.5484	39.6774
GLM	0.0987	0.0809	91.6129	16.1290
MM	0.4910	0.2086	44.8387	42.2581
MV-probit	0.1442	0.0857	43.2258	42.5806
OLS	0.0998	0.0818	91.9355	17.0968
Tobit	0.1213	0.0720	41.6129	38.3871
Two-part	0.0965	0.0777	90.9677	14.5161

Table 3

b. Comparison of mapping model derived from development dataset – SF-36v2 to EQ-5D-5L

Model	RMSE	MAE	AE > 0.05 (%)	AE > 0.10 (%)
Basic model				
1compartment ALDVMM with summary scores	0.0968	0.0715	51.6667	21.0000
1compartment ALDVMM with 8 domain scores	0.0878	0.0654	49.0000	23.0000
2compartment ALDVMM with summary scores	0.0988	0.0776	61.0000	19.0000
2compartment ALDVMM with 8 domain scores	0.0892	0.0721	51.3333	20.0000
3compartment ALDVMM with summary scores	0.0998	0.0782	62.3333	19.0000
3compartment ALDVMM with 8 domain scores	0.0897	0.0745	55.1495	19.9336
Beta with summary scores	0.0969	0.0763	64.0000	18.3333
Beta with 8 domain scores	0.0881	0.0694	49.6667	21.3333
CLAD with summary scores	0.1012	0.0627	43.6667	28.0000
CLAD with 8 domain scores	0.4081	0.3344	79.0000	75.6667
MNL with summary scores	0.0948	0.0737	57.3333	16.6667
MNL with 8 domain scores	0.0855	0.0671	50.3333	17.0000
OLS with summary scores	0.0950	0.0706	52.3333	19.3333
OLS with 8 domain scores	0.0874	0.0648	49.6667	19.6667
Tobit with summary scores	0.1097	0.0646	41.0000	32.3333
Tobit with 8 domain scores	0.0979	0.0590	39.0000	31.0000
Two-part with summary scores	0.0961	0.0714	50.6667	19.3333
Two-part with 8 domain scores	0.0882	0.0659	47.6667	20.3333
Model with demographic covariates				
1compartment ALDVMM with summary scores	0.0966	0.0714	50.0000	20.6667
1compartment ALDVMM with 8 domain scores	0.0871	0.0648	47.3333	22.3333
2compartment ALDVMM with summary scores	0.0985	0.0773	65.6667	20.0000
2compartment ALDVMM with 8 domain scores	0.0882	0.0740	57.7558	20.1320
3compartment ALDVMM with summary scores	0.0985	0.0764	65.0000	19.3333
3compartment ALDVMM with 8 domain scores	0.0874	0.0712	50.6579	18.4211
Beta with summary scores	0.0967	0.0762	65.0000	18.3333
Beta with 8 domain scores	0.0891	0.0703	48.0000	23.0000
CLAD with summary scores	0.2689	0.1904	65.0000	59.0000
CLAD with 8 domain scores	0.1389	0.1152	74.6667	63.3333
MNL with summary scores	0.0947	0.0730	58.6667	15.6667
MNL with 8 domain scores	0.0840	0.0657	51.0000	17.6667
OLS with summary scores	0.0948	0.0704	53.6667	18.6667
OLS with 8 domain scores	0.0869	0.0646	51.0000	19.0000
Tobit with summary scores	0.1097	0.0645	41.6667	33.0000
Tobit with 8 domain scores	0.0972	0.0584	40.0000	31.3333
Two-part with summary scores	0.0960	0.0710	51.3333	19.0000
Two-part with 8 domain scores	0.0874	0.0652	48.0000	21.3333

Table 4
a. Comparison of mapping model by internal validation – HAQ-DI to EQ-5D-5L

Model	Mean	SD	maximum	median	minimum	RMSE	MAE	AIC	BIC	AE > 0.05 (%)	AE > 0.10 (%)	ICC
Basic model												
1compartment ALDVMM	0.9225	0.0657	0.9458	0.9458	0.5596	0.0904	0.0798	152.1075	163.3172	96.0784	18.6275	0.493
2compartment ALDVMM	0.9146	0.0753	0.9386	0.9386	0.5153	0.0927	0.0830	7.4280	33.5840	97.0588	18.6275	0.505
3compartment ALDVMM	0.9126	0.0747	0.9336	0.9336	0.5116	0.0945	0.0856	0.3038	41.4061	98.0392	21.5686	0.483
Beta	0.9121	0.0676	0.9353	0.9353	0.5364	0.0905	0.0817	-1144.5066	-1133.2969	95.0980	18.6275	0.497
CLAD	0.9689	0.0747	1.0000	1.0000	0.5840	0.1044	0.0679			46.0784	37.2549	0.465
GLM	0.9137	0.0579	0.9391	0.9391	0.6302	0.0872	0.0784	-479.4677	-468.2580	91.1765	15.6863	0.495
MM	0.8777	0.2943	1.0000	1.0000	-0.6380	0.2483	0.1130	-404.3373	-393.1276	46.0784	39.2157	0.377
MV-probit	0.9817	0.1060	1.0000	1.0000	0.3520	0.1344	0.0849	6051.7911	6398.9864	44.1176	44.1176	0.345
OLS	0.9141	0.0608	0.9394	0.9394	0.6010	0.0877	0.0789	-542.9433	-531.7336	94.1176	14.7059	0.501
Tobit	0.9754	0.0800	1.0000	1.0000	0.5317	0.1126	0.0720	158.7196	169.9294	44.1176	43.1373	0.423
Two-part	0.9141	0.0623	0.9448	0.9448	0.6546	0.0863	0.0745	357.1480 / -270.7789	364.6212 / -262.0409	87.2549	15.6863	0.523
Model with demographic covariates												
1compartment ALDVMM	0.9223	0.0655	0.9477	0.9450	0.5588	0.0904	0.0799	156.0591	174.7420	96.0784	18.6275	0.492
2compartment ALDVMM	0.9166	0.0664	0.9404	0.9371	0.5295	0.0910	0.0819	11.8816	52.9839	97.0588	18.6275	0.487
3compartment ALDVMM	0.9158	0.0698	0.9394	0.9388	0.5073	0.0908	0.0815	7.3353	67.1204	97.0588	17.6471	0.503
Beta	0.9117	0.0668	0.9386	0.9340	0.5345	0.0904	0.0819	-1140.9051	-1122.2222	96.0784	18.6275	0.495
CLAD	0.9844	0.0361	1.0000	1.0000	0.7836	0.1155	0.0757			46.0784	44.1176	0.261
GLM	0.9129	0.0576	0.9456	0.9365	0.6280	0.0875	0.0788	-475.8773	-457.1944	91.1765	13.7255	0.491
MM	0.8012	0.4777	1.0000	1.0000	-1.6650	0.4359	0.1827	-271.2695	-252.5866	47.0588	43.1373	0.242
MV-probit	0.9802	0.1030	1.0000	1.0000	0.3930	0.1292	0.0817	6045.5420	6546.0700	44.1176	43.1373	0.376
OLS	0.9136	0.0606	0.9438	0.9376	0.5998	0.0879	0.0792	-539.1391	-520.4562	92.1569	16.6667	0.498
Tobit	0.9753	0.0799	1.0000	1.0000	0.5304	0.1126	0.0720	162.6576	181.3405	44.1176	43.1373	0.422
Two-part	0.9136	0.0624	0.9499	0.9431	0.6533	0.0867	0.0750	361.0561 / -267.1073	376.0024 / -252.5440	86.2745	15.6863	0.518

Table 4
b. Comparison of mapping model by internal validation - SF-36v2 to EQ-5D-5L

Model	Mean	SD	maximum	median	minimum	RMSE	MAE	AIC	BIC	AE > 0.05 (%)	AE > 0.10 (%)	ICC
Basic model												
1compartment ALDVMM with summary scores	0.9169	0.0734	0.9742	0.9478	0.6164	0.0934	0.0695	113.5007	128.3158	49.5050	17.8218	0.486
1compartment ALDVMM with 8 domain scores	0.9116	0.0891	0.9901	0.9498	0.6001	0.1020	0.0732	92.2015	129.2394	53.4653	22.7723	0.467
2compartment ALDVMM with summary scores	0.9155	0.0663	0.9534	0.9447	0.5911	0.1000	0.0782	-2.0453	31.2888	59.4059	15.8416	0.374
2compartment ALDVMM with 8 domain scores	0.9049	0.0894	0.9653	0.9497	0.5460	0.1083	0.0809	-19.9967	57.7827	54.4554	18.8119	0.403
3compartment ALDVMM with summary scores	0.9160	0.0701	0.9527	0.9463	0.5816	0.1028	0.0802	-3.8710	47.9819	62.3762	16.8317	0.359
3compartment ALDVMM with 8 domain scores	0.9109	0.0750	0.9602	0.9484	0.6340	0.1052	0.0792	-31.9257	86.7018	55.0000	18.0000	0.491
Beta with summary scores	0.9097	0.0631	0.9554	0.9373	0.6291	0.0952	0.0757	-1116.9495	-1083.6155	64.3564	13.8614	0.419
Beta with 8 domain scores	0.9064	0.0825	0.9744	0.9406	0.5788	0.1070	0.0793	-1189.9613	-1112.1819	53.4653	23.7624	0.379
CLAD with summary scores	0.9378	0.0811	1.0000	0.9769	0.6456	0.0956	0.0601			45.5446	22.7723	0.511
CLAD with 8 domain scores	0.5850	0.2604	1.0000	0.3930	0.3930	0.4374	0.3791			84.1584	83.1683	-0.020
MNL with summary scores	0.9009	0.0642	0.9610	0.9227	0.6984	0.0911	0.0725	1437.3037	1603.9739	51.4851	18.8119	0.479
MNL with 8 domain scores	0.8933	0.0887	0.9738	0.9290	0.5684	0.1049	0.0766	-591.3330	-554.2952	53.4653	20.7921	0.447
OLS with summary scores	0.9085	0.0681	0.9787	0.9310	0.6794	0.0887	0.0676	-553.0345	-538.2194	47.5248	19.8020	0.516
OLS with 8 domain scores	0.9064	0.0813	1.0210	0.9334	0.6563	0.0972	0.0713	-591.3330	-554.2952	50.4950	22.7723	0.483
Tobit with summary scores	0.9542	0.0839	1.0000	1.0000	0.6066	0.1057	0.0620	121.0312	135.8463	40.5941	29.7030	0.446
Tobit with 8 domain scores	0.9402	0.0998	1.0000	1.0000	0.5911	0.1118	0.0686	99.7251	136.7629	46.5347	30.6931	0.436
Two-part with summary scores	0.9079	0.0709	0.9739	0.9368	0.6867	0.0877	0.0668	331.5214 / -261.4394	342.6327 / -249.9386	46.5347	15.8416	0.538
Two-part with 8 domain scores	0.9049	0.0838	0.9923	0.9386	0.6513	0.0966	0.0709	322.5703 / -270.3651	355.9044 / -241.6131	50.4950	24.7525	0.500
Model with demographic covariates												
1compartment ALDVMM with summary scores	0.9176	0.0728	0.9747	0.9492	0.6138	0.0925	0.0688	116.9136	139.1363	49.5050	16.8317	0.494

Model	Mean	SD	maximum	median	minimum	RMSE	MAE	AIC	BIC	AE > 0.05 (%)	AE > 0.10 (%)	ICC
Basic model												
1compartment ALDVMM with 8 domain scores	0.9124	0.0886	0.9921	0.9477	0.5977	0.1002	0.0720	93.3730	137.8184	52.4752	23.7624	0.484
2compartment ALDVMM with summary scores	0.9159	0.0638	0.9575	0.9424	0.5842	0.0981	0.0761	0.3311	48.4803	61.3861	13.8614	0.385
2compartment ALDVMM with 8 domain scores	0.9222	0.0640	0.9637	0.9465	0.6263	0.1058	0.0783	-20.6145	72.2288	58.1633	18.3673	0.424
3compartment ALDVMM with summary scores	0.9158	0.0589	0.9559	0.9432	0.6712	0.0976	0.0777	-20.1368	50.2350	63.3663	16.8317	0.367
3compartment ALDVMM with 8 domain scores	0.9285	0.0534	0.9657	0.9509	0.6357	0.1091	0.0824	-97.6168	39.9133	53.6082	24.7423	0.337
Beta with summary scores	0.9101	0.0622	0.9548	0.9362	0.6265	0.0943	0.0748	-1109.8339	-1061.6847	65.3465	13.8614	0.425
Beta with 8 domain scores	0.9007	0.0890	0.9793	0.9381	0.5675	0.1107	0.0813	-1192.4475	-1099.8529	57.4257	25.7426	0.377
CLAD with summary scores	0.7712	0.2536	1.0000	0.9073	0.3930	0.3029	0.2286			76.2376	68.3168	0.043
CLAD with 8 domain scores	0.8162	0.0644	0.9171	0.8384	0.5861	0.1347	0.1145			74.2574	61.3861	0.287
MNL with summary scores	0.9000	0.0708	0.9627	0.9253	0.5641	0.0911	0.0725	1462.1184	1739.9021	58.4158	16.8317	0.507
MNL with 8 domain scores	0.8955	0.0910	0.9818	0.9293	0.5649	0.1056	0.0752	1491.1100	2102.2340	53.4653	19.8020	0.449
OLS with summary scores	0.9093	0.0680	0.9800	0.9333	0.6776	0.0876	0.0665	-549.9638	-527.7411	48.5149	15.8416	0.528
OLS with 8 domain scores	0.9073	0.0817	1.0288	0.9241	0.6759	0.0958	0.0697	-590.5618	-546.1164	50.4950	23.7624	0.499
Tobit with summary scores	0.9547	0.0831	1.0000	1.0000	0.6037	0.1049	0.0614	124.4753	146.6980	40.5941	29.7030	0.452
Tobit with 8 domain scores	0.9409	0.0994	1.0000	1.0000	0.5886	0.1110	0.0682	100.9645	145.4099	45.5446	32.6733	0.443
Two-part with summary scores	0.9086	0.0713	0.9760	0.9394	0.6866	0.0866	0.0655	334.2489 / -257.4700	352.7678 / -240.2188	46.5347	15.8416	0.552
Two-part with 8 domain scores	0.9059	0.0839	0.9942	0.9357	0.6647	0.0951	0.0692	323.6449 / -266.7634	364.3865 / -232.261	51.4851	22.7723	0.516

External validation

The models derived from the development dataset were applied without modification to the independent sample of 394 participants who visited after the first visit. Results of external validation were presented in Table 5. The two-part model demonstrated the best performance for the HAQ-DI and the SF-36v2.

Table 5
a. External validation of mapping model from HAQ-DI to EQ-5D-5L utility score

Model	Mean	SD	maximum	median	minimum	RMSE	MAE	AE > 0.05 (%)	AE > 0.10 (%)
Basic model									
1compartment ALDVMM	0.9253	0.0610	0.9458	0.9458	0.4812	0.0836	0.0728	97.4619	12.6904
2compartment ALDVMM	0.9160	0.0718	0.9386	0.9386	0.4984	0.0863	0.0768	97.2081	14.2132
3compartment ALDVMM	0.9131	0.0708	0.9336	0.9336	0.4988	0.0886	0.0796	98.7310	14.9746
Beta	0.9148	0.0625	0.9353	0.9353	0.4697	0.0851	0.0763	97.2081	12.6904
CLAD	0.9733	0.0713	1.0000	1.0000	0.4880	0.0933	0.0544	37.8173	30.7107
GLM	0.9174	0.0558	0.9391	0.9391	0.5747	0.0812	0.0725	93.1472	11.1675
MM	0.8949	0.2806	1.0000	1.0000	-1.0160	0.2345	0.1012	38.5787	36.0406
MV-probit	0.9892	0.0789	1.0000	1.0000	0.3390	0.1253	0.0714	38.3249	38.0711
OLS	0.9177	0.0580	0.9394	0.9394	0.5229	0.0819	0.0730	94.9239	11.4213
Tobit	0.9770	0.0752	1.0000	1.0000	0.4120	0.0994	0.0577	37.3096	33.5025
Two-part	0.9189	0.0614	0.9448	0.9448	0.6150	0.0790	0.0686	91.1168	11.4213
Model with demographic covariates									
1compartment ALDVMM	0.9253	0.0608	0.9481	0.9453	0.4820	0.0835	0.0727	97.4619	12.9442
2compartment ALDVMM	0.9188	0.0619	0.9508	0.9373	0.4922	0.0866	0.0763	96.9543	12.4365
3compartment ALDVMM	0.9161	0.0720	0.9442	0.9388	0.4941	0.0862	0.0763	97.2081	13.7056
Beta	0.9149	0.0618	0.9447	0.9345	0.4703	0.0850	0.0762	97.2081	12.6904
CLAD	0.9866	0.0356	1.0000	1.0000	0.7336	0.1041	0.0604	37.8173	35.5330
GLM	0.9173	0.0556	0.9563	0.9374	0.5746	0.0812	0.0723	92.3858	10.9137
MM	0.8295	0.4561	1.0210	1.0000	-2.2800	0.4130	0.1625	39.5939	37.3096
MV-probit	0.9862	0.0812	1.0000	1.0000	0.3390	0.1184	0.0681	37.5635	37.0558
OLS	0.9176	0.0577	0.9463	0.9383	0.5238	0.0818	0.0730	94.1624	11.4213
Tobit	0.9770	0.0748	1.0000	1.0000	0.4135	0.0994	0.0576	37.0558	33.5025
Two-part	0.9188	0.0610	0.9499	0.9436	0.6185	0.0788	0.0685	91.3706	11.4213

Table 5
b. External validation of mapping model from SF-36v2 to EQ-5D-5L utility score

Model	Mean	SD	maximum	median	minimum	RMSE	MAE	AE > 0.05 (%)	AE > 0.10 (%)	ICC
Basic model										
1compartment ALDVMM with summary scores	0.9290	0.0656	0.9774	0.9563	0.5360	0.0753	0.0601	41.7553	15.4255	0.6149
1compartment ALDVMM with 8 domain scores	0.9304	0.0750	0.9885	0.9626	0.5670	0.0772	0.0595	43.3511	20.7447	0.6288
2compartment ALDVMM with summary scores	0.9245	0.0558	0.9566	0.9476	0.5519	0.0798	0.0689	57.9787	13.8298	0.5299
2ompartament ALDVMM with 8 domain scores	0.9220	0.0718	0.9693	0.9518	0.5601	0.0813	0.0689	49.4681	15.9574	0.5774
3compartment ALDVMM with summary scores	0.9247	0.0580	0.9558	0.9481	0.5573	0.0807	0.0699	59.3085	13.5638	0.5284
3compartment ALDVMM with 8 domain scores	0.9216	0.0680	0.9611	0.9518	0.5498	0.0821	0.0687	44.4149	17.2872	0.5533
Beta with summary scores	0.9195	0.0549	0.9583	0.9425	0.5815	0.0779	0.0671	61.9681	12.7660	0.5509
Beta with 8 domain scores	0.9247	0.0655	0.9759	0.9535	0.6254	0.0800	0.0641	46.0106	17.8191	0.5659
CLAD with summary scores	0.9519	0.0731	1.0000	0.9917	0.5858	0.0788	0.0488	38.0319	22.3404	0.6187
CLAD with 8 domain scores	0.6126	0.2636	1.0000	0.4023	0.3930	0.4245	0.3599	82.9787	81.3830	-0.0027
MNL with summary scores	0.9106	0.0656	0.9641	0.9384	0.4159	0.0769	0.0649	51.8617	14.3617	0.6072
MNL with 8 domain scores	0.9108	0.0833	0.9772	0.9456	0.4096	0.0856	0.0650	44.4149	16.2234	0.5854
OLS with summary scores	0.9214	0.0629	0.9868	0.9442	0.6209	0.0744	0.0589	44.6809	15.4255	0.6171
OLS with 8 domain scores	0.9244	0.0716	1.0127	0.9499	0.6401	0.0767	0.0573	45.2128	17.2872	0.6227
Tobit with summary scores	0.9663	0.0741	1.0000	1.0000	0.5077	0.0880	0.0519	35.9043	28.9894	0.5532
Tobit with 8 domain scores	0.9600	0.0827	1.0000	1.0000	0.5533	0.0884	0.0537	39.8936	28.7234	0.5709
Two-part with summary scores	0.9214	0.0646	0.9782	0.9498	0.6663	0.0748	0.0593	42.2872	14.6277	0.6179
Two-part with 8 domain scores	0.9230	0.0741	0.9899	0.9562	0.6745	0.0776	0.0580	41.2234	17.8191	0.6220
Model with demographic covariates										
1compartment ALDVMM with summary scores	0.9290	0.0661	0.9808	0.9576	0.5435	0.0753	0.0601	42.8191	15.6915	0.6165
1compartment ALDVMM with 8 domain scores	0.9303	0.0769	0.9922	0.9622	0.5807	0.0780	0.0599	44.4149	20.4787	0.6274
2compartment ALDVMM with summary scores	0.9245	0.0556	0.9600	0.9472	0.5985	0.0794	0.0682	60.9043	12.5000	0.5340
2ompartament ALDVMM with 8 domain scores	0.9254	0.0625	0.9635	0.9497	0.6031	0.0829	0.0711	54.2553	15.6915	0.5207
3compartment ALDVMM with summary scores	0.9240	0.0524	0.9601	0.9469	0.6759	0.0817	0.0689	61.9681	13.8298	0.4943
3compartment ALDVMM with 8 domain scores	0.9256	0.0697	0.9692	0.9539	0.5855	0.0836	0.0696	47.0745	17.0213	0.5434
Beta with summary scores	0.9196	0.0551	0.9591	0.9429	0.5958	0.0778	0.0669	59.5745	12.7660	0.5535
Beta with 8 domain scores	0.9203	0.0726	0.9828	0.9529	0.6152	0.0819	0.0646	46.2766	18.6170	0.5742
CLAD with summary scores	0.7930	0.2311	1.0000	0.8781	0.3930	0.2617	0.1836	63.0319	57.1809	0.1663
CLAD with 8 domain scores	0.8259	0.0660	0.9989	0.8474	0.5434	0.1347	0.1168	78.1915	67.5532	0.2845
MNL with summary scores	0.9115	0.0643	0.9680	0.9367	0.4753	0.0752	0.0635	50.7979	12.5000	0.6191
MNL with 8 domain scores	0.9095	0.0871	0.9854	0.9456	0.4723	0.0884	0.0664	46.8085	18.0851	0.5750
OLS with summary scores	0.9216	0.0636	0.9965	0.9460	0.6236	0.0743	0.0587	46.0106	14.3617	0.6197
OLS with 8 domain scores	0.9250	0.0733	1.0182	0.9455	0.6460	0.0771	0.0571	45.7447	17.8191	0.6246
Tobit with summary scores	0.9661	0.0745	1.0000	1.0000	0.5181	0.0879	0.0518	35.6383	28.7234	0.5550

Model	Mean	SD	maximum	median	minimum	RMSE	MAE	AE > 0.05 (%)	AE > 0.10 (%)	ICC
Basic model										
Tobit with 8 domain scores	0.9595	0.0845	1.0000	1.0000	0.5700	0.0892	0.0543	39.3617	29.2553	0.5705
Two-part with summary scores	0.9215	0.0652	0.9834	0.9502	0.6632	0.0747	0.0592	41.2234	16.4894	0.6213
twopart_2_SF8	0.9234	0.0753	0.9939	0.9550	0.6741	0.0780	0.0582	41.7553	17.2872	0.6231

Final model selection

The final model was selected based on the development process, internal validation, and external validation. Two-part model was selected as the final mapping algorithm from the HAQ-DI and SF-36v2.

The coefficient estimates for final selected model were presented in Table 6-a and Table 6-b.

Table 6
a. Coefficient of best performance mapping model from HAQ-DI to Eq-5D-5L

	Two-part			Two-part (w. sex, age)								
	Full health			Non-Full health			Full health			Non-Full health		
	Estimate	SE	p	Estimate	SE	p	Estimate	SE	p	Estimate	SE	p
Intercept	0.7641	0.1379	< 0.001	0.8264	0.0090	< 0.001	0.7203	0.9636	0.4547	0.8156	0.0493	< 0.001
HAQ_DI	-5.8355	1.0782	< 0.001	-0.1057	0.0174	< 0.001	-5.8577	1.0831	< 0.001	-0.1071	0.0178	< 0.001
Sex							-0.1013	0.8178	0.9015	-0.0064	0.0411	0.8765
Age							0.0029	0.0101	0.7760	0.0003	0.0006	0.5764

Table 6
a. Coefficient of best performance mapping model from SF-36v2 to Eq-5D-5L

	Two-part			Two-part (w. sex, age)								
	Full health			Non Full health			Full health			Non Full health		
	Estimate	SE	p	Estimate	SE	p	Estimate	SE	p	Estimate	SE	p
Intercept	-9.5539	1.4322	< 0.001	0.5493	0.0447	< 0.001	-9.0444	1.7019	< 0.001	0.5484	0.0715	< 0.001
PCS_T	0.1274	0.0195	< 0.001	0.0042	0.0008	< 0.001	0.1268	0.0196	< 0.001	0.0042	0.0008	< 0.001
MCS_T	0.0700	0.0179	< 0.001	0.0013	0.0007	0.0456	0.0735	0.0184	< 0.001	0.0013	0.0007	0.0507
Sex							-0.0333	0.8054	0.9670	-0.0039	0.0410	0.9243
Age							-0.0121	0.0108	0.2643	0.0001	0.0006	0.8766

Discussion

This study developed and validated the first algorithms mapping the HAQ-DI and the SF-36v2 onto EQ-5D-5L utility scores in patients with gout, using the Korean value set [10]. Both source measures are widely administered in gout research and routine rheumatology practice [28], but neither is preference-based so that could not generate the utility scores required for QALY estimation [11]. Various candidate models were evaluated, providing that the two-part model was best performance for the HAQ-DI and the SF-36v2.

The performance of two-part model was consistent with the distributional characteristics of the utility data reported above. Utility scores were left-skewed, limited at 1, and clustered at full health in 56.07% of observations. The observed distribution did not satisfy the assumptions of normality and constant variance which OLS depends on. Rather than fitting a single distribution across this structure, the two-part model separates it into the two processes. The first part model was constructed with patients who reported no problems on any of the five dimensions, and the second part model was constructed with patients who reported at least one problem [29]. This decomposition suggested the way EQ-5D-5L data arises in practice, distinguishing patients reporting full health from patients who do not [30].

Comparison across predictor sets showed that those using only the PCS and MCS were better than using eight SF-36v2 domain scores, indicating that summary scores were more widely reported, giving the algorithm broader applicability. The inclusion of age and sex slightly improved predictive performance. Their inclusion is consistent with ISPOR Good Practice recommendations for avoiding model misspecification, and with evidence that both were associated with HRQoL of gout patients [1, 2, 11].

The principal strengths of this study were summarized by four points. First, the algorithms were developed in a gout-specific population using the Korean value set, addressing both the disease specificity and the country specificity [10, 11, 18]. Second, regression methods ranged across direct, indirect, and mixture-based approaches, which were compared under a common set of performance criteria [11, 12]. Third, model selection was supported by both

internal validation and external validation in an independent sample of 394 participants. Finally, recruitment across 13 hospitals with competitive enrolment at sites improved the representativeness of the sample relative to single-center studies [31].

Limitations

There were several limitations in this study. First, the sample contained few participants in severely affected health states, so the algorithms overestimate utility at the lower end of the range. Predictions regressed toward the sample mean, so utility score was overestimated for patients in the severe health state. Second, over 50% of participants reported that they had full health causing underestimation in predicted utility score. The selected two-part model calculated utility score considering non-full health participants, participants who reported full health can be interpreted as having more problems. Finally, comorbidities are common in gout and may affect EQ-5D-5L utility but may not be fully captured by the HAQ-DI and SF-36v2. Therefore, the mapping model may not fully account for health effects unrelated to gout, potentially leading to underestimation of utility in patients with little or no comorbidity and overestimation in those with a substantial comorbidity burden.

Conclusion

The algorithms to predict utility scores from HAQ-DI and SF-36v2 were developed based on Korean gout patients. The performance of models was better with two-part models in mapping both HAQ-DI and SF-36v2. The algorithms from this study can predict health utility scores when no preference-based health utility scores are available. The predicted value can be used in health economic evaluations, which contribute the effective resource allocation in medical decision-making.

Abbreviations

AE
Absolute Error
AIC
Akaike Information Criterion
ALDMMM
Adjusted Limited Dependent Variable Mixture Model
BIC
Bayesian Information Criterion
BP
Bodily Pain
CLAD
Censored Least Absolute Deviations
GH
General Health
GLM
Generalized Linear Model
HAQ-DI
Health Assessment Questionnaire Disability Index
HRQoL
Health-Related Quality of Life
ICC
Intraclass Correlation Coefficient
MAE
Mean Absolute Error
MCS
Mental Component Summary
MH
Mental Health
MNL
Multinomial Logit Model
MV-probit
Multivariate Probit Model
OLS
Ordinary Least Squares
PCS
Physical Component Summary
PF
Physical Functioning
QALY

Quality-Adjusted Life Year
RE
Role-Emotional
RMSE
Root Mean Squared Error
RP
Role-Physical
SD
Standard Deviation
SF
Social Functioning
SF-36v2
36-Item Short Form Health Survey, Version 2
VT
Vitality

Declarations

Supplementary information The online version contains supplementary material available at ###.

Competing Interests

The authors declare no competing interests.

Ethics approval

This study was performed in line with principles of the Declaration of Helsinki. Approval was granted by the Institutional Review Board of Ewha Womans University (approval no. ewha-202504-0032-01)-

Consent to participate

Informed consent was obtained from all individual participants included in the study.

Consent to publish

Not applicable

Data Availability Statement

The datasets are available from the corresponding author on reasonable request.

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Author Contribution

All authors contributed to the study conception and design. Material preparation and data collection were performed by Sangyoon Shin, Doyeon Jin, Suhyeon Noh, and Hyorim Lee. Data analysis was conducted by Sangyoon Shin and Jeonghoon Ahn. The first draft of the manuscript was written by Sangyoon shin and Jeonghoon Ahn. All authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Figures

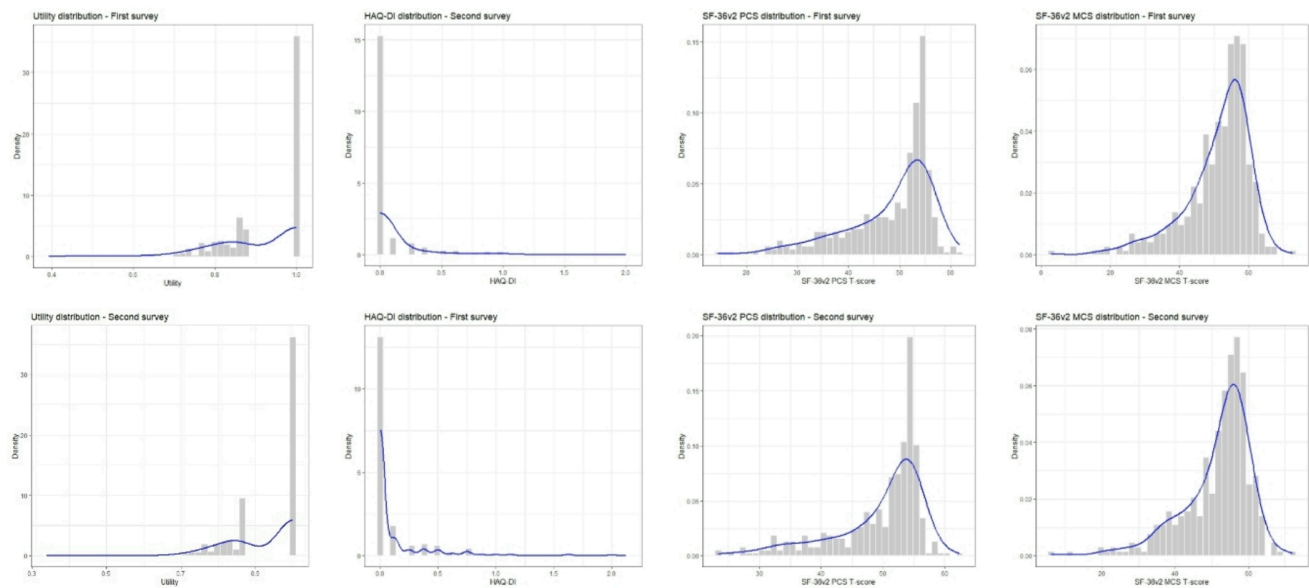


Figure 1

Distribution of HRQoL instruments score