

Association of Toll-Like Receptor 9 Gene Polymorphisms With Remission in Patients With Rheumatoid Arthritis Receiving Tumor Necrosis Factor Alpha Inhibitors and Development of Machine Learning Models

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Research Article

Keywords: Gene, polymorphisms, patients, rheumatoid arthritis, machine, human leukocyte antigen (HLA)

Posted Date: May 27th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-534605/v1>

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Abstract

Studies that investigate the association between toll-like receptor (TLR)-4 or TLR9 gene polymorphisms and remission from the disease in RA patients taking tumor necrosis factor alpha (TNF- α) inhibitors have yet to be conducted. In this context, this study was designed to investigate the effects of polymorphisms in TLR4 and TLR9 on response to TNF- α inhibitor and develop various machine learning approaches to predict remission. A total of six single nucleotide polymorphisms (SNPs) were investigated. Logistic regression analysis was used to investigate the association between genetic polymorphisms and response to treatment. Various machine learning methods were utilized for prediction of remission. After adjusting for covariates, the rate of remission of T-allele carriers of TLR9 rs352139 was about 5 times that of the CC-genotype carriers (95% confidence interval (CI) 1.325–19.231, $p = 0.018$). Among machine learning algorithms, multivariate logistic regression and elastic net showed the best prediction with the AUROC value of 0.71 (95% CI 0.597 - 0.823 for both models). This study showed an association between a TLR9 polymorphism (rs352139) and treatment response in RA patients receiving TNF- α inhibitors. Moreover, this study developed various machine learning methods for prediction, among which the elastic net provided the best model for remission prediction.

Introduction

Rheumatoid arthritis (RA) is a severe chronic inflammatory reaction that occurs in the synovium of joints. Mortality hazards are 60–70% higher in patients with RA than in those without the disease [1]. Although the exact etiology of RA is still under investigation, several genetic studies have suggested a role of genetic factors [2, 3]. The most well-known genetic risk factors for RA are variations in the human leukocyte antigen (HLA) genes, especially the HLA-DRB1 gene [4]. However, many other genes with potential links to RA remain to be investigated in order to discover further genetic risk factors and therapeutic variations for RA.

Tumor necrosis factor alpha (TNF- α) inhibitors play important roles in inflammatory states, including RA [5]. There are five TNF- α inhibitors available for RA treatment (adalimumab, certolizumab, etanercept, golimumab, and infliximab), and clinical efficacies in RA are known to be similar among these agents [6]. Patients with advanced RA are treated with TNF- α inhibitors; however, the efficacy of these treatments is still questionable as several studies have reported that only one-third of the patients benefit from the treatment [7, 8].

Toll-like receptors (TLRs) play vital roles in both innate and acquired immune systems [9], and several studies have shown their association with the development of RA [10–12]. Notably, TLRs are known as inducers of TNF- α transcription [13]. Triad3A is an E3 ubiquitin–protein ligase that induces degradation of TLR4 and TLR9 [14]. Hence, reduction in endogenous Triad3A results in TLR activation. Since Triad3A acts specifically on TLR4 and TLR9 among the 13 members of the TLR family, the genes encoding TLR4 and TLR9 are important for understanding RA pathogenesis and potential therapeutic intervention [15–18].

Nuclear factor-kappaB (NFkB) is associated with the response to TNF- α inhibitors in autoimmune diseases [19]. Because of this role of NFkB, several transcription factors activating NFkB have been discovered and investigated, including TLRs. As TLRs activate pro-inflammatory cytokines including TNF- α and transcription factors such as NFkB, their polymorphisms may potentially affect treatment outcomes [20]. Therefore, this study aimed to examine the effects of TLR4 and TLR9 polymorphisms on drug response in RA patients receiving TNF- α inhibitors. Moreover, we developed machine learning algorithms to assess the ability of the obtained factors to predict remission in patients with RA.

Methods

Study patients

This prospective observational two-center study enrolled 105 patients who were prescribed TNF- α inhibitors (adalimumab, etanercept, golimumab, or infliximab) at Ajou University Hospital and Chungbuk National University Hospital between July 2017 and December 2019. Data collection was conducted using electronic medical records. Data on sex, age, weight, height, duration of RA, autoantibodies against rheumatoid factor, anti-cyclic citrullinated peptide, concomitant medications, and comorbidities were collected from electronic medical records. Additionally, baseline data on disease activity score (DAS)-28 and its subcomponents, which included tender joint count (TJC)-28, swollen joint count (SJC)-28, global health (GH), and erythrocyte sedimentation rate (ESR) or C-reactive protein levels, were collected.

A good clinical response to anti-TNF therapy was defined as basis of the DAS-28 scores. Patients with a DAS-28 score of less than 2.6 after 6 months of TNF- α inhibitor therapy, were considered to be in remission [21]. DAS-28 was calculated as $0.56 \times \sqrt{(\text{TJC}28)} + 0.28 \times \sqrt{(\text{SJC}28)} + 0.70 \times \ln(\text{ESR}) + 0.014 \times \text{GH}$ [21].

This study was approved by the Institutional Review Boards of the Ajou University Hospital (approval number: AJIRB-BMR-OBS-17-153) and Chungbuk National University Hospital (approval number: 2017-06-011-004). All patients submitted written informed consents for participation. This study was conducted according to the principles of the Declaration of Helsinki (2013).

Genotyping methods

To select single nucleotide polymorphisms (SNPs) of TLR4 and TLR9 that might be associated with RA remission, genetic information on TLR4 and TLR9 was obtained from the PharmGKB database, Haploreg 4.1, the NCBI Database of SNPs (dbSNP), and previous studies [19, 22-26]. A total of six SNPs, including four SNPs of TLR4 (rs11536889, rs1927907, rs1927911, and rs2149356) and two SNPs of TLR9 (rs352139 and rs352140), were selected.

Genomic DNA of the patients was isolated from ethylenediaminetetraacetic acid–blood samples using the QIAamp DNA Blood Mini Kit (Qiagen GmbH, Hilden, Germany) according to the manufacturer's protocol. Genotyping was performed using a single-base primer extension assay with SNaPSHOT

multiplex kits (ABI, Foster City, CA, USA) or TaqMan genotyping assay in a real-time PCR system (ABI 7300, ABI), according to the manufacturer's recommendations.

Statistical analysis and machine learning methods

Student's *t*-test was used to compare continuous variables between patients who showed good clinical response (remission) and those who did not. Chi-square test or Fisher's exact test was used to compare categorical variables between the two groups. Multivariable logistic regression analysis was used to examine independent factors for remission; factors with a *p*-value less than 0.05 in univariate analysis along with clinically relevant confounders were included in multivariable analysis. The Hosmer–Lemeshow test was performed to confirm the model's goodness of fit.

This study employed a random forest–based classification approach to analyze the importance of different variables for factors that affect remission. To prevent over-fitting, we selected seven features that are most important. Various machine learning methods such as multivariate logistic regression, elastic net, random forest, and support vector machine (SVM) were utilized for prediction of remission. All the methods were implemented with the caret R package. The area under the receiver-operating curve (AUROC), to assess the ability of the risk factor to predict complication, and its 95% confidence interval (CI) of each machine learning prediction models were described in this study. A *p*-value of less than 0.05 was considered statistically significant. Univariate statistical analysis was conducted using IBM SPSS statistics, version 20 software (International Business Machines Corp., New York, USA). All other analyses were performed using R software version 3.6.0 (R Foundation for Statistical Computing, Vienna, Austria).

To measure performance of each machine learning model, internal validation was done. The dataset was randomly divided for model development and evaluation in prediction process. After partitioning one data sample into five subsets, one subset was selected for model validation while the remaining subsets were used to establish machine learning models. Each five-fold cross-validation iteration was repeated 100 times to evaluate the power of the machine learning models.

Results

Among the 105 patients enrolled in this study, 7 patients were excluded due to incomplete medical data. The data from 98 patients receiving TNF- α inhibitors were analyzed. The mean age of the included patients was 53 years (range: 20–82 years), and there were 79 (80.6%) females. The mean duration of RA was 9 years, and 29 patients reached remission. To determine the possible effect of the disease status on response to TNF- α inhibitors, baseline DAS-28 and its subcomponents were examined. Baseline DAS-28 and its subcomponents were not statistically significant between the remission and non-remission groups (Table 1). Marginal significance was found according to sex (*p* = 0.059) and hypertension (*p* = 0.060).

Table 1
Patient characteristics according to the response at 6 months treatment of TNF inhibitors

Characteristics, n (%)	Remission (n = 29)	No remission (n = 69)	p-value
Sex			0.059
Male	9 (31.0)	10 (14.5)	
Female	20 (69.0)	59 (85.5)	
Age	51.4 ± 13.4	53.6 ± 13.9	0.399
< 65	26 (89.7)	53 (76.8)	0.142
≥ 65	3 (10.3)	16 (23.2)	
BMI, kg/m ²	23.4 ± 3.0	22.3 ± 3.8	0.220
< 23	13 (44.8)	42 (60.9)	0.144
≥ 23	16 (55.2)	27 (39.1)	
Duration of rheumatoid arthritis, months	103.9 ± 87.8	111.0 ± 69.2	0.666
Rheumatoid factor			0.329
Positive	20 (69.0)	54 (78.3)	
Negative	9 (31.0)	15 (21.7)	
ACPA			0.177
Positive	17 (34.6)	49 (79.0)	
Negative	9 (65.4)	13 (21.0)	
Concomitant drug			
Hydroxychloroquine			0.902
Yes	16 (55.2)	39 (56.5)	
No	13 (44.8)	30 (43.5)	
Leflunomide			0.665
Yes	10 (34.5)	27 (39.1)	
No	19 (65.5)	42 (60.9)	

BMI: body mass index; ACPA: anticyclic citrullinated peptide antibody

DAS28: disease activity score 28 joints; ESR: erythrocyte sedimentation rate; CRP: C-reactive protein

Characteristics, n (%)	Remission (n = 29)	No remission (n = 69)	<i>p</i> -value
Methotrexate			0.319
Yes	19 (65.5)	52 (75.4)	
No	10 (34.5)	17 (24.6)	
Sulfasalazine			0.111
Yes	7 (24.1)	7 (10.1)	
No	22 (75.9)	62 (89.9)	
Tacrolimus			0.986
Yes	5 (17.2)	12 (17.4)	
No	24 (82.8)	57 (82.6)	
Comorbidity			
Diabetes			0.669
Yes	1 (3.6)	5 (7.2)	
No	27 (96.4)	64 (92.8)	
Dyslipidemia			1.000
Yes	3 (10.7)	9 (13.0)	
No	25 (89.3)	60 (87.0)	
Hypertension			0.060
Yes	1 (3.6)	14 (20.3)	
No	27 (96.4)	55 (79.7)	
Osteoporosis			0.725
Yes	4 (14.3)	7 (10.1)	
No	24 (85.7)	62 (89.9)	
Vitamin D deficiency			0.272
Yes	1 (3.6)	9 (13.0)	
No	27 (96.4)	60 (87.0)	

BMI: body mass index; ACPA: anticyclic citrullinated peptide antibody

DAS28: disease activity score 28 joints; ESR: erythrocyte sedimentation rate; CRP: C-reactive protein

Characteristics, n (%)	Remission (n = 29)	No remission (n = 69)	<i>p</i> -value
Baseline DAS28 with its subcomponents			
DAS28	5.8 ± 1.2	5.8 ± 1.1	0.696
Tender joint count 28	9.6 ± 8.3	10.7 ± 74.3	0.782
Swollen joint count 28	6.6 ± 7.1	7.5 ± 5.7	0.872
Global health	55.3 ± 18.5	62.4 ± 20.2	0.167
ESR	54.7 ± 29.5	49.5 ± 27.3	0.379
CRP	3.0 ± 4.4	2.1 ± 2.5	0.113
BMI: body mass index; ACPA: anticyclic citrullinated peptide antibody			
DAS28: disease activity score 28 joints; ESR: erythrocyte sedimentation rate; CRP: C-reactive protein			

As shown in Table 2, statistically significant associations between genotypes and RA remission were found for both TLR9 SNPs: T-allele carriers of rs352139 and rs352140 experienced approximately 3.3 and 4.5 times more frequent remission than patients with the CC genotype, respectively.

Table 2
Genotype association with the remission at 6 months treatment of
TNF inhibitors

Gene, rs number	Remission (DAS28 < 2.6)	No remission (DAS28 ≥ 2.6)	<i>p</i>-value
TLR4 rs11536889			0.578
GG, CG	11 (39.3)	23 (33.3)	
CC	17 (60.7)	46 (66.7)	
TLR4 rs1927907			1.000
CC, CT	27 (93.1)	64 (92.8)	
TT	2 (6.9)	5 (7.2)	
TLR4 rs1927911			0.178
AA, AG	21 (72.4)	40 (58.0)	
GG	8 (27.6)	29 (42.0)	
TLR4 rs2149356			0.335
TT, TG	21 (72.4)	56 (81.2)	
GG	8 (27.6)	13 (18.8)	
TLR9 rs352139			0.017
TT, CT	25 (89.3)	45 (65.2)	
CC	3 (10.7)	24 (34.8)	
TLR9 rs352140			0.008
TT, CT	26 (92.9)	46 (66.7)	
CC	2 (7.1)	23 (33.3)	
TLR: toll-like receptor; TNF- α : tumor necrosis factor- α			

Multivariable analysis (Table 3) included sex, age, and factors with $p < 0.05$ from the univariate analysis. Because significant linkage disequilibrium was observed between rs352139 and rs352140 ($r^2 = 0.95$), only rs352139 was included in the multivariable analysis. Among the included factors, rs352139 was significantly associated with RA remission (95% CI 1.325–19.231, $p = 0.018$). After adjusting for related covariates, the remission rate in T-allele carriers of rs352139 was about 5.1 times that in patients with the CC genotype. The Hosmer–Lemeshow test showed that the fitness of the multivariable analysis model was satisfactory ($\chi^2 = 0.907$, 2 degrees of freedom, $p = 0.636$).

Table 3
Multivariate analysis to identify predictors for the remission rate at 6 months treatment of TNF inhibitors

	Crude OR (95% CI)	p-value	Adjusted OR (95% CI)	p-value
Age < 65	2.618 (0.699–9.803)	0.153		
Male	2.653 (0.944–7.462)	0.064		
TLR9 rs352139 ^a	4.444 (1.217–16.129)	0.024	5.05 (1.325–19.231)	0.018
a. T carriers of rs352139				
Adjusted for age, sex, and TLR9 rs352139.				
OR: odds ratio; CI: confidence interval				

As shown in Figure 1, after feature selection using performing five-fold cross-validated random forest approach, four important variables from feature selection (rs352139, body mass index (BMI), sulfasalazine, and anti-citrullinated protein/peptide antibody (AC-PA)) were included in machine learning models.

After performing five-fold cross-validated multivariate logistic regression, elastic net, random forest, support vector machine (SVM) models, the average area under the receiver-operating curve (AUROC), values across 100 random iterations were shown in Table 4.

Table 4
Comparisons of AUC for logistic regression, elastic net, random forest, and SVM models

	AUROC	95% CI
Logistic regression	0.71	0.594–0.827
Elastic net	0.71	0.594–0.827
Random Forest	0.70	0.584–0.821
SVM (Linear)	0.60	0.416–0.782
SVM (Radial)	0.67	0.530–0.813
AUROC: area under the receiver-operating curve; CI: confidence interval; SVM: Support vector machine		

The AUROC values for multivariate logistic regression, elastic net, and random forest indicated good performances of the models; 0.71, 0.71, and 0.70 respectively (95% CI 0.594 - 0.827 for multivariate logistic regression and elastic models and 0.584 - 0.821, respectively). Linear kernel SVM and radial kernel SVM revealed sub-optimal performances of the models; AUROC values of 0.60 and 0.67, respectively (95% CI 0.416 - 0.782 and 0.53 - 0.813, respectively). Figure 2 showed AUROC curves of three models that exhibit good interpretability and prediction rate.

Discussion

The main finding of this study is that rs352139 of TLR9 was associated with treatment response to TNF- α inhibitors in RA patients. The remission rate in T-allele carriers of rs352139 was about 5 times that in patients with the CC genotype. Multivariate logistic regression and elastic net were proven to be the most suitable method in predicting remission in patients with RA, with AUROC values of 0.71 (95% CI 0.594–0.827 for both models).

TNF- α is a pro-inflammatory cytokine involved in the innate immune response [27]. It is involved in the pathogenesis of several inflammatory conditions, especially RA. As the TNF- α level is elevated in patients with RA, TNF- α inhibitors have been frequently used to treat RA. Unlike other agents for RA therapy, TNF- α inhibitors target cytokines and are used to treat patients with advanced RA.

Damage-associated molecular patterns (DAMPs) are endogenous danger molecules that activate the innate immune system by interacting with TLRs. This evokes innate immune responses, including induction of inflammatory cytokines [28]. DAMPs play an important role in the initiation of inflammation during tissue injury without infection and may also be involved in chronic inflammation including autoimmune diseases [12]. Once DAMPs are released during tissue injury, TLRs are activated, and the inflammatory cycle is initiated. The binding of TLRs to DAMPs activates the receptors, up-regulating pro-inflammatory mediators including cytokines and resulting in various inflammatory conditions and chronic inflammation [12].

Ligand-bound TLRs interact with elements on the surface of pathogens and activate the MyD88-related pathways [28], resulting in NF κ B activation and cytokine gene expression [10]. This ultimately leads to the induction of molecules associated with inflammation and release of pro-inflammatory components such as TNF- α [29]. TLRs are known as inducers of TNF- α transcription [13]. Several studies have shown an increased expression of TLR4 on RA synovial fluid macrophages and RA synovial fibroblasts [30, 31] and of TLR9 in RA synovial tissue fibroblasts and RA peripheral blood monocytes [18, 32].

Our results revealed that TLR9 polymorphism was associated with the remission rate of RA patients taking TNF- α inhibitors. The T-allele carriers of rs352139 had a significantly higher remission rate than patients with the CC genotype. TLR9 is expressed by B cells and functions with the B cell receptor complex, resulting in the release of rheumatoid factor [33]. Previously, Bank et al. [19] have reported an association of the GG genotype of rs352139 with nonresponse to TNF- α inhibitors in inflammatory bowel disease patients, which is in line with our findings. This association is possibly attributable to alteration in TLR function; however, further research is required to validate our results, as there are no published mechanistic studies on the association between this polymorphism and TNF- α inhibition or treatment response in advanced RA patients.

The utilization of machine learning approaches to predict remission in patients with RA receiving TNF- α inhibitors is novel in clinical research. In clinical settings, these models can be helpful in decision-making process. To overcome over-fitting, this study utilized random forest, an ensemble method of bootstrap

aggregated binary classification trees [34] for feature selection. We also demonstrated that multivariate logistic regression and elastic net, a penalized linear regression model that combine penalties of the lasso and ridge methods [35], models outperformed other models. Hence, these models may be useful in predicting remission in patients on TNF- α inhibitor treatment.

The limitations of our study are its small sample size and a lack of a detailed mechanism. Nevertheless, to our knowledge, this is the first study to investigate the effects of genetic variations in the TLR4 and TLR9 genes on favorable response rates to RA treatment in patients taking TNF- α inhibitors. Moreover, this study provides important features and prediction models based on machine learning algorithms including logistic regression, elastic net, random forest and SVM for remission in patients with RA receiving TNF- α inhibitors. Thus, our current results could be used as preliminary data to design individually tailored TNF- α inhibitor treatments for RA patients.

Declarations

Acknowledgement

This work was supported by the Basic Science Research Program (NRF-2020R1F1A1069718) through the National Research Foundation of Korea funded by the Ministry of Science, ICT & Future Planning and Medical Research Center Program. This study was supported by "Regional Innovation Strategy(RIS)" through the National Research Foundation of Korea(NRF) funded by the Ministry of Education(MOE). The funding sources did not have a role in the design, conduct, and analysis of the study.

Author Contributions

Conceptualization: WK, JHK, IA, HK, JJ, KEL; Methodology: WK, THK, JJ, KEL; Formal analysis and investigation: WK, HJK, SJO; Writing - original draft preparation: WK, THK; Writing - review and editing: JHK, IAC, HK; Funding acquisition: KEL; Resources: IAC, HK, JJ; Supervision: IAC, KEL

Competing interests

The author(s) declare no competing interests.

References

1. Dadoun, S. *et al.* Mortality in rheumatoid arthritis over the last fifty years: systematic review and meta-analysis. *Joint Bone Spine*. **80**, 29–33 (2013).
2. Coenen, M. J. H. & Gregersen, P. K. Rheumatoid arthritis: a view of the current genetic landscape. *Genes Immun*. **10**, 101–111 (2009).
3. Raychaudhuri, S. *et al.* Genetic variants at CD28, PRDM1 and CD2/CD58 are associated with rheumatoid arthritis risk. *Nat Genet*. **41**, 1313–1318 (2009).

4. NIH.gov [Internet]. Genetics Home Reference. Your Guide to Understanding Genetic Conditions. Rheumatoid arthritis. [updated 18 August 2020; cited 1 October 2020]. Available from: <https://medlineplus.gov/genetics/condition/rheumatoid-arthritis/>.
5. Gerriets, V. *et al.* Tumor Necrosis Factor Inhibitors. [Updated 2020 Jul 4]. In: StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing; 2020 Jan-. Available from: <https://www.ncbi.nlm.nih.gov/books/NBK482425/>
6. Mitoma, H., Horiuchi, T., Tsukamoto, H. & Ueda, N. Molecular mechanisms of action of anti-TNF- α agents - Comparison among therapeutic TNF- α antagonists. *Cytokine*. **101**, 56–63 (2018).
7. Rutgeerts, P. *et al.* Infliximab for induction and maintenance therapy for ulcerative colitis. *N Engl J Med*. **353**, 2462–2476 (2005).
8. Mascheretti, S. *et al.* Pharmacogenetic investigation of the TNF/TNF-receptor system in patients with chronic active Crohn's disease treated with infliximab. *Pharmacogenomics J*. **2**, 127–136 (2002).
9. Li, M., Zhou, Y., Feng, G. & Su, S. The critical role of Toll-like receptor signaling pathways in the induction and progression of autoimmune diseases. *Curr Mol Med*. **9**, 365–374 (2009).
10. Huang, Q. & Pope, R. M. The role of toll-like receptors in rheumatoid arthritis. *Curr Rheumatol Rep*. **11**, 357–364 (2009).
11. McCormack, W. J., Parker, A. E. & O'Neill, L. A. Toll-like receptors and NOD-like receptors in rheumatic diseases. *Arthritis Res Ther*. **11**, 243 (2009).
12. Goh, F. G. & Midwood, K. S. Intrinsic danger: activation of Toll-like receptors in rheumatoid arthritis. *Rheumatology (Oxford)*. **51**, 7–23 (2012).
13. Falvo, J. V., Tsytsykova, A. V. & Goldfeld, A. E. Transcriptional control of the TNF gene. *Curr Dir Autoimmun*. **11**, 27–60 (2010).
14. Chuang, T. & Ulevitch, R. J. Triad3A, an E3 ubiquitin-protein ligase regulating Toll-like receptors. *Nat Immunol*. **5**, 495–502 (2004).
15. Sanchez-Pernaute, O. *et al.* Citrullination enhances the pro-inflammatory response to fibrin in rheumatoid arthritis synovial fibroblasts. *Ann Rheum Dis*. **72**, 1400–1406 (2013).
16. Ospelt, C. *et al.* Overexpression of toll-like receptors 3 and 4 in synovial tissue from patients with early rheumatoid arthritis: toll-like receptor expression in early and longstanding arthritis. *Arthritis Rheum*. **58**, 3684–3692 (2008).
17. Radstake, T. R. D. J. *et al.* Expression of toll-like receptors 2 and 4 in rheumatoid synovial tissue and regulation by proinflammatory cytokines interleukin-12 and interleukin-18 via interferon-gamma. *Arthritis Rheum*. **50**, 3856–3865 (2004).
18. Jongbloed, S. L. *et al.* Enumeration and phenotypical analysis of distinct dendritic cell subsets in psoriatic arthritis and rheumatoid arthritis. *Arthritis Res Ther*. **8**, R15 (2006).
19. Bank, S. *et al.* Associations between functional polymorphisms in the NF κ B signaling pathway and response to anti-TNF treatment in Danish patients with inflammatory bowel disease. *Pharmacogenomics J*. **14**, 526–534 (2014).

20. Akira, S., Takeda, K. & Kaisho, T. Toll-like receptors: critical proteins linking innate and acquired immunity. *Nat Immunol.* **2**, 675–680 (2001).
21. Salaffi, F. & Ciapetti, A. Clinical disease activity assessments in rheumatoid arthritis. *Int. J. Clin Rheumatol.* **8**, 347–360 (2013).
22. Whirl-Carrillo, M. *et al.* Pharmacogenomics Knowledge for Personalized Medicine. *Clinical Pharmacology & Therapeutics.* **92**, 414–417 (2012).
23. Ward, L. D. & Kellis, M. HaploReg v4: systematic mining of putative causal variants, cell types, regulators and target genes for human complex traits and disease. *Nucleic Acids Res.* **44**, D877–881 (2016).
24. Sherry, S. T. *et al.* dbSNP: the NCBI database of genetic variation. *Nucleic Acids Res.* **29**, 308–311 (2001).
25. Davis, M. L. R. *et al.* Associations of toll-like receptor (TLR)-4 single nucleotide polymorphisms and rheumatoid arthritis disease progression: an observational cohort study. *Int Immunopharmacol.* **24**, 346–352 (2015).
26. Wang, Z. *et al.* Influence of TLR4 rs1927907 locus polymorphisms on tacrolimus pharmacokinetics in the early stage after liver transplantation. *Eur J Clin Pharmacol.* **70**, 925–931 (2014).
27. Clark, I. A. How TNF was recognized as a key mechanism of disease. *Cytokine Growth Factor Rev.* **18**, 335–343 (2007).
28. Akira, S., Uematsu, S. & Takeuchi, O. Pathogen recognition and innate immunity. *Cell.* **124**, 783–801 (2006).
29. Kawai, T. & Akira, S. TLR signaling. *Cell Death Differ.* **13**, 816–825 (2006).
30. Huang, Q., Ma, Y., Adebayo, A. & Pope, R. M. Increased macrophage activation mediated through toll-like receptors in rheumatoid arthritis. *Arthritis Rheum.* **56**, 2192–21201 (2007).
31. Kim, K. W. *et al.* Human rheumatoid synovial fibroblasts promote osteoclastogenic activity by activating RANKL via TLR-2 and TLR-4 activation. *Immunol Lett.* **110**, 54–64 (2007).
32. Hu, F. *et al.* Hypoxia and hypoxia-inducible factor-1alpha provoke toll-like receptor signalling-induced inflammation in rheumatoid arthritis. *Annals of the Rheumatic Diseases.* **73**, 928–936 (2014).
33. Chaturvedi, A., Dorward, D. & Pierce, S. K. The B cell receptor governs the subcellular location of Toll-like receptor 9 leading to hyperresponses to DNA-containing antigens. *Immunity.* **28**, 799–809 (2008).
34. Breiman, L. Random forests. *Mach. Learn.* **45**, 5–32 (2001).
35. Zou, H. & Hastie, T. "Regularization and Variable Selection via the Elastic Net". *J R Stat Soc Ser B.* **67**, 301–320 (2005).

Figures

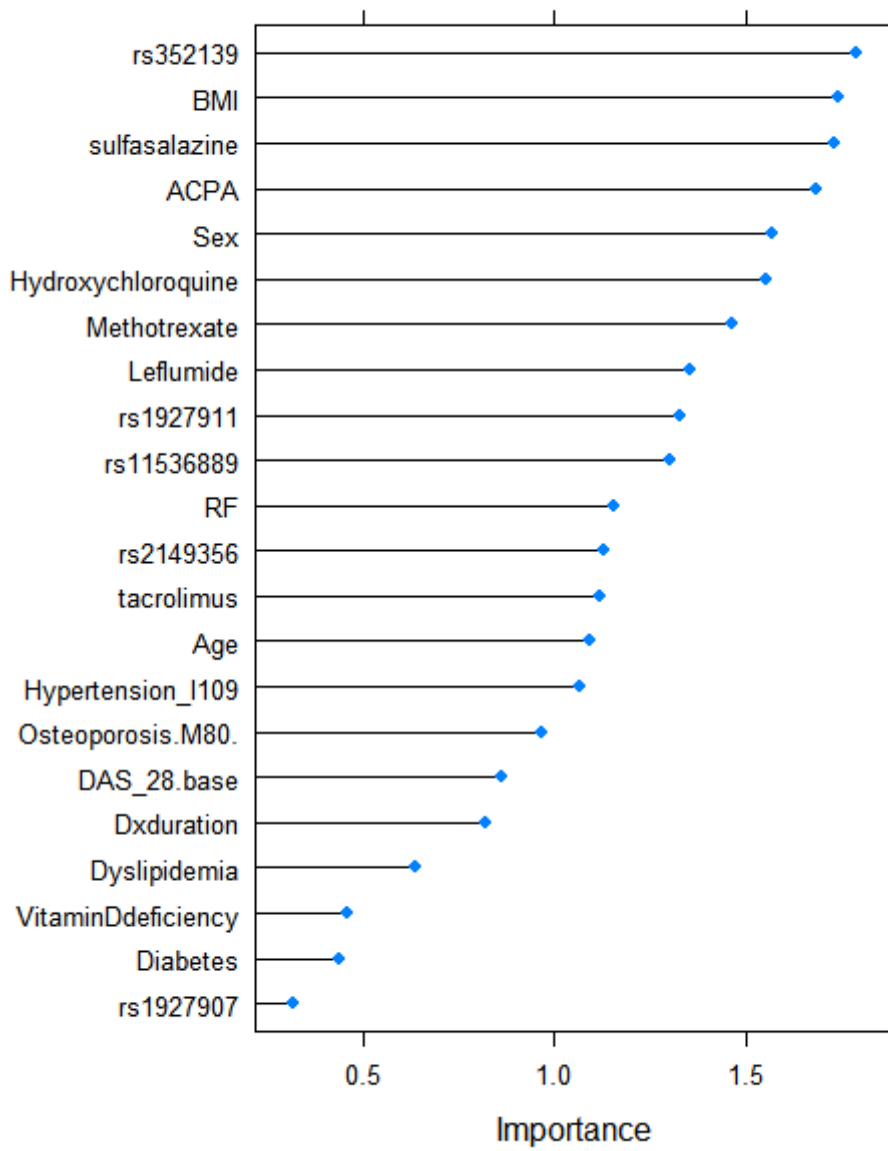


Figure 1

Variable importance using random forest to predict remission in patients with RA receiving TNF- α inhibitors

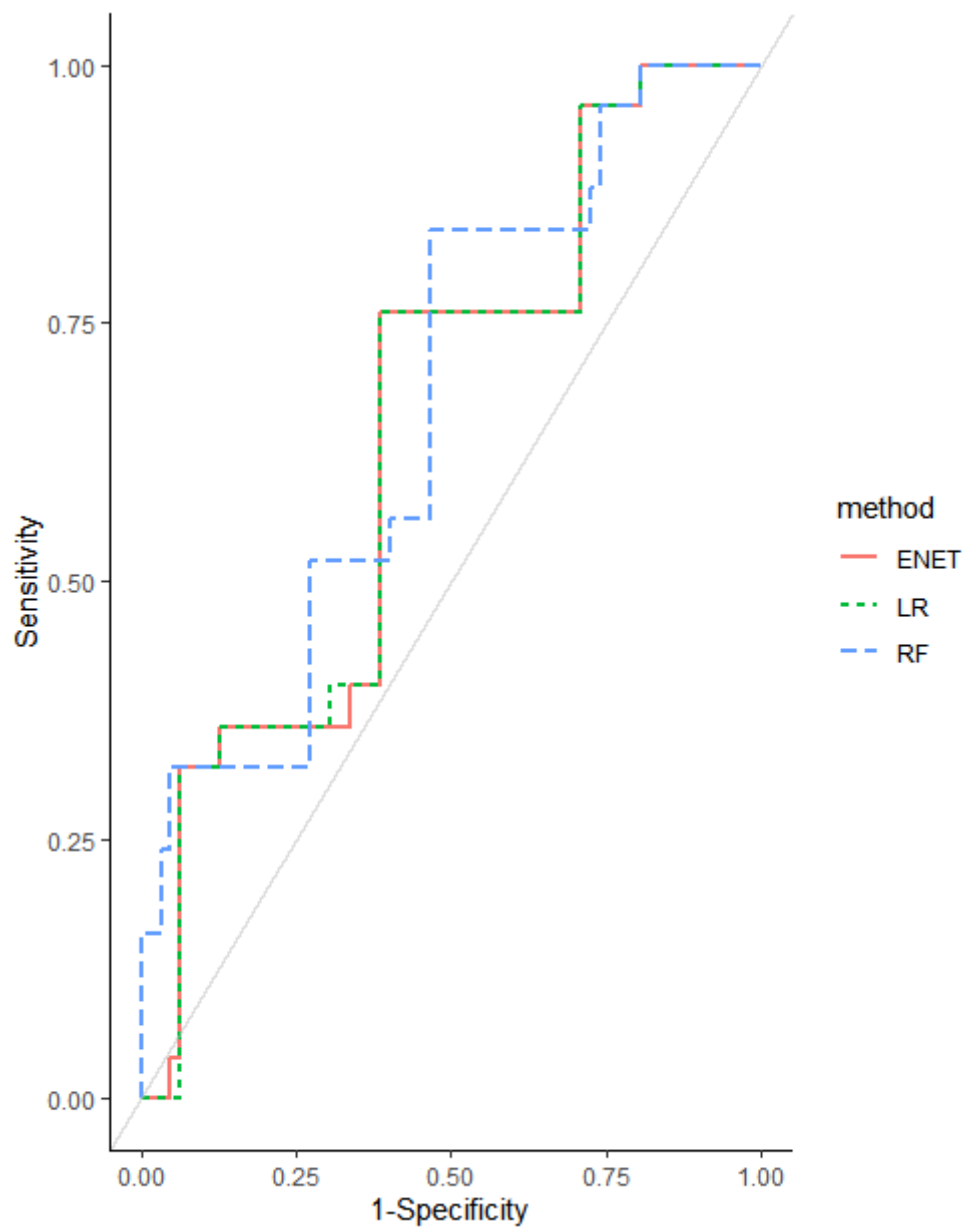


Figure 2

The receiver operating characteristic curves for predictive performance of elastic net (ENET), logistic regression (LR), and random forest (RF) models