Conclusions A decision tree model that includes age, gender, AFP, platelet counts, and GGT is useful for predicting the probability of response to therapy with peg-interferon plus ribavirin and has the potential to support clinical decisions regarding the selection of patients for therapy.

Keywords Data mining · Decision tree · Alpha-fetoprotein · HCV · Peg-interferon

Introduction

The current standard therapy for genotype 1 chronic hepatitis C is 48 weeks of pegylated interferon (PEG-IFN) plus ribavirin (RBV) [1]. Sustained virological response (SVR), defined as undetectable HCVRNA post-treatment is regarded as a cure of chronic hepatitis C. However, the rate of SVR to this regimen is only 50% in patients with HCV genotype 1b and a high HCVRNA titer [2, 3]. Since PEG-IFN and RBV combination therapy is costly and accompanied by potential adverse effects, the ability to predict the possibility of SVR before therapy may significantly influence the selection of patients for therapy. A recent report revealed that single nucleotide polymorphisms located in the *IL28B* are strongly associated with a response to PEG-IFN plus RBV therapy [4–6]. Besides, the amino acid substitutions in the NS5A [7–9] or core region of HCV were also associated with response to therapy [10, 11]. Unfortunately, these host genetic and viral factors are not yet readily available for general application in actual clinical practice. Fibrosis of the liver is also an important predictor of response, but resources may be limited in some countries. Clinical and non-invasive parameters may be better suited for general practice, but there is no established means by which the likelihood of a response can be predicted prior to therapy.

Data mining is a method of predictive analysis that explores data, without setting the hypothesis, to discover hidden patterns and relationships in highly complex datasets and enables the development of predictive models. Decision tree analysis is a core component of data mining and predictive modeling [12], and it is utilized by decision makers in various fields of business. Recent publications on decision tree analysis indicate its usefulness for defining prognostic factors in various diseases such as prostate cancer [13], diabetes [14], melanoma [15, 16], colorectal carcinoma [17, 18], and liver failure [19]. The results of the analysis are presented as a tree structure, which is intuitive and facilitates the allocation of patients into subgroups by following the flow chart form [20]. We have recently reported the usefulness of decision tree analysis for the prediction of early virological response (undetectable HCVRNA within 12 weeks of therapy) to PEG-IFN and RBV combination therapy in chronic hepatitis C [21].

In the present study, we used decision tree analysis to explore baseline predictors of response to PEG-IFN/RBV therapy so that a pre-treatment algorithm could be created to discriminate chronic hepatitis C patients who are likely to respond to PEG-IFN/RBV therapy from those who are not. For the purpose of use in general practice, only clinical and non-invasive parameters were included in the analysis.

Materials and methods

Patients

This was a multicenter retrospective cohort study supported by the Japanese Ministry of Health, Labor and Welfare. Data were collected from a total of 800 chronic hepatitis C patients who received therapy for 48 weeks with PEG-IFN alpha-2b and RBV at Musashino Red Cross Hospital, Toranomon Hospital, Tokyo Medical and Dental University, Osaka University, Nagoya City University Graduate School of Medical Sciences, Yamanashi University, and their related hospitals. The inclusion criteria to be enrolled in this study were as follows (1) infection by genotype 1b, (2) HCVRNA higher than 100,000 IU/ml by quantitative PCR (Cobas Amplicor HCV Monitor v 2.0, Roche Diagnostic systems, CA), which is typically used for the definition of high viral load in Japan, (3) lack of co-infection with hepatitis B virus or human immunodeficiency virus, (4) lack of other causes of liver disease such as autoimmune hepatitis and primary biliary cirrhosis and (5) completion of at least 12 weeks of therapy. Patients received PEG-IFN alpha-2b (1.5 μg/kg) subcutaneously every week and were administered a weight-adjusted dose of RBV (600 mg for <60 kg, 800 mg for 60–80 kg, and 1;000 mg for >80 kg), which is the recommended dosage in Japan. Patients who were treated for more than 49 weeks were not included in the study. For the analysis, patients were randomly assigned to either the model building ($n = 506$) or the internal validation ($n = 295$) group. Consent was obtained from each patient. The study protocol conformed to the ethical guidelines of the Declaration of Helsinki and was approved by the institutional review committee. The baseline characteristics and representative laboratory test results are listed in Table 1. The overall rate of SVR was 47% in the model building set and 49% in the validation set. There were no significant differences in the clinical backgrounds between these 2 groups.

For external validation of the model, we collaborated with another study group supported by the Japanese Ministry of Health, Labor and Welfare. This multicenter study group consisted of 29 medical centers and hospitals

Table 1 Comparison of pre-treatment factors between model building and internal validation patients

	Model ($n = 506$)	Validation ($n = 295$)
Age (years)	56 (14–75)	55 (18–74)
Male gender[a]	261/506 (52%)	160/295 (54%)
Body mass index (kg/m^2)	22.9 (14.3–34.0)	23.2 (16.1–33.8)
Albumin (g/dl)	4 (2.7–5.0)	4 (2.8–4.9)
Creatinine (mg/dl)	0.7 (0.4–1.5)	0.7 (0.4–1.1)
AST (IU/l)	60 (11–370)	62 (11–240)
ALT (IU/l)	73 (11–413)	73 (14–390)
GGT (IU/l)	56 (10–328)	55 (7–409)
Total cholesterol (mg/dl)	173 (73–297)	171 (29–273)
Triglyceride (mg/dl)	105 (33–474)	109 (32–372)
White blood cell count (/μl)	4,745 (1,800–10,900)	4,823 (1,200–9,700)
Neutrophil count (/μl)	2,563 (667–7,870)	2,484 (508–7,579)
Red blood cell count (/μl)	448 (313–577)	451 (313–574)
Hemoglobin (g/dl)	14.1 (9.4–18.3)	14.1 (10.0–18.0)
Hematocrit (%)	41.7 (13.3–53.7)	41.9 (15.5–52.7)
Platelets (10^9/l)	164 (52–380)	158 (43–312)
AFP (ng/ml)	14.7 (0.9–680)	13 (0.8–323)
HCVRNA (10^3 IU/ml)	1,852 (100–5,100)	1,870 (100–5,100)
Fibrosis stage: F3–4	73/417 (18%)	48/247 (19%)

Data expressed as median (range) unless otherwise indicated

AST aspartate aminotransferase, *ALT* alanine aminotransferase, *GGT* gamma-glutamyltransferase, *AFP* alpha-fetoprotein

[a] Data expressed as number/available data (percentage)

belonging to the National Hospital Organization. A dataset collected from 524 patients who were treated with PEG-IFN alpha-2b/RBV was used as an external validation dataset, i.e., completely independent from the dataset that was used for model building.

Laboratory tests

Blood samples were obtained before therapy and at least once every month during therapy, and were used for hematologic tests, blood chemistry analysis and determination of HCV RNA. Pretreatment levels of HCV RNA were quantified by Cobas Amplicor (Roche Diagnostic Systems, Pleasanton, CA). SVR was defined as undetectable HCV RNA at week 24 after completion of therapy, as determined by qualitative PCR with a lower end detection limit of 50 IU/ml (Amplicor, Roche Diagnostic Systems). Liver biopsy was available in 664 patients. Fibrosis and activity were scored according to the METAVIR scoring system [22]. Fibrosis was staged on a scale of 0–4: F0 (no fibrosis), F1 (mild fibrosis: portal fibrosis without septa), F2 (moderate fibrosis: few septa), F3 (severe fibrosis: numerous septa without cirrhosis) and F4 (cirrhosis). Activity of necroinflammation was graded on a scale of 0–3: A0 (no activity), A1 (mild activity), A2 (moderate activity) and A3 (severe activity).

Statistical analysis

A database of pretreatment variables was created containing 6 variables from hematological tests (red blood cells, hemoglobin, hematocrit, white blood cells, neutrocytes and platelets), 8 variables from the blood chemistry test [creatinine, albumin, aspartate aminotransferase, alanine aminotransferase, gamma-glutamyltransferase (GGT), total cholesterol, triglyceride and alpha-fetoprotein (AFP)], serum level of HCV RNA and 3 variables for patient characteristics (age, gender and body mass index). Based on this database, the recursive partitioning analysis algorithm referred to as decision tree analysis was implemented to define meaningful subgroups of patients with respect to the possibility of achieving SVR.

Decision tree analysis is a family of nonparametric regression methods. Software is used to automatically explore the data to search for optimal split variables and to build a decision tree structure [23]. For the analysis, the entire study population was evaluated to determine which variables and cutoff points yielded the most significant division into 2 prognostic subgroups that were as homogeneous as possible for the probability of SVR. Thereafter, the same analytic process was applied to all newly defined subgroups. A restriction was imposed on the tree construction such that the procedure stopped when either no additional significant variable was detected or when the sample size was below 20. For this analysis, the data mining software IBM SPSS Modeler 13 (IBM SPSS Inc., Chicago, IL) was utilized. SPSS software v.15.0 (SPSS Inc., Chicago, IL) was used for multivariate logistic regression analysis.

Results

Decision tree analysis

Decision tree analysis was carried out on the model building dataset from 506 patients using 18 variables. Figure 1 shows the results. The analysis automatically selected 5 predictive variables to produce a total of 7 subgroups of patients. Age was selected as the variable of initial split with an optimal cutoff of 50 years. The possibility of achieving SVR was 41% for patients older than 50 compared to 70% for patients

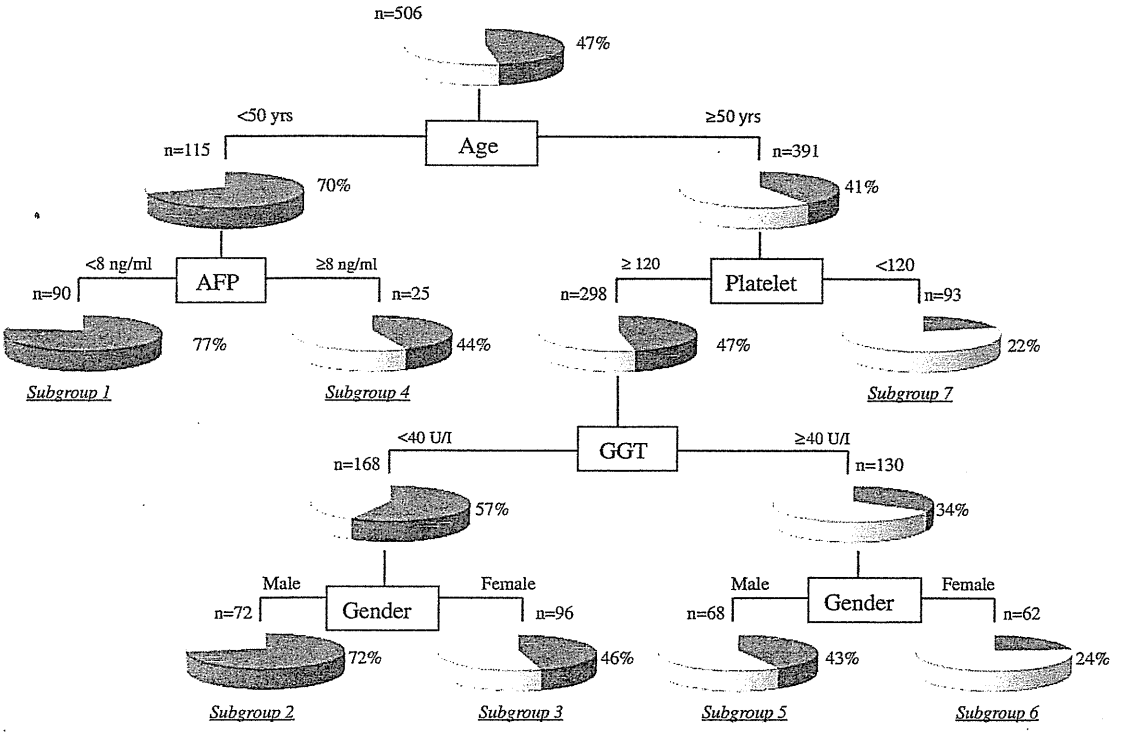

Fig. 1 Decision tree analysis. *Boxes* indicate the factors for splitting and the cutoff value for the split. *Pie charts* indicate the rate of SVR for each group. Terminal subgroups of patients discriminated by the analysis are numbered from 1 to 7. *AFP* alpha-fetoprotein, *GGT* gamma-glutamyltransferase

younger than 50. Among patients younger than 50, the level of serum AFP, with an optimal cutoff of 8 ng/ml, was selected as the variable of second split. Patients with lower AFP levels had a higher probability of SVR (77 vs. 44%). Among older patients, platelet count was selected as the second variable of split, with an optimal cutoff of 120×10^9/l. Patients with higher platelet counts had a higher probability of SVR (47 vs. 22%). Among patients with platelet counts higher than 120×10^9/l, GGT was selected as the third variable of split with an optimal cutoff of 40 IU/l. Patients with a lower GGT level had a higher probability of SVR (57 vs. 34%). Gender was selected as the fourth variable of split, with male gender being a predictor of a higher SVR probability (72 vs. 46% in patients with GGT levels <40 IU/l and 43 vs. 24% in those with GGT ≥40 IU/l). HCVRNA load was included in the analysis but was not selected as a significant variable.

The probabilities of SVR for the 7 subgroups derived by this process were highly variable. The subgroup of young patients (<50 years) with low serum AFP (<8 ng/ml) (subgroup 1) or the subgroup of older (≥50 years) male patients with high platelet counts ($\geq 120 \times 10^9$/l) and low serum GGT (<40 IU/l) (subgroup 2) showed the highest probability of SVR (72 and 77%), while the subgroup of older (≥50 years) patients with low platelet counts ($<120 \times 10^9$/l) (subgroup 7) and older (≥50 years) female patients with high serum GGT (subgroup 6) showed the lowest probability of SVR (22 and 24%).

Validation of the decision tree

The results of the decision tree analysis were validated with an internal validation dataset of 295 cases, which was independent of the model building dataset. Each patient in the validation set was allocated to subgroups 1–7 using the flow-chart form of the decision tree. The rates of SVR were 77% for subgroup 1, 71% for subgroup 2, 55% for subgroup 3, 44% for subgroup 4, 41% for subgroup 5, 17% for subgroup 6, and 30% for subgroup 7. The rates of SVR for each subgroup of patients were closely correlated between the model building dataset and the internal validation dataset ($r^2 = 0.925$) (Fig. 2a).

To further confirm the universality of the results, data collected from 524 patients by a collaborating study group were used for external validation. Thus, the dataset used for external validation was completely independent of the

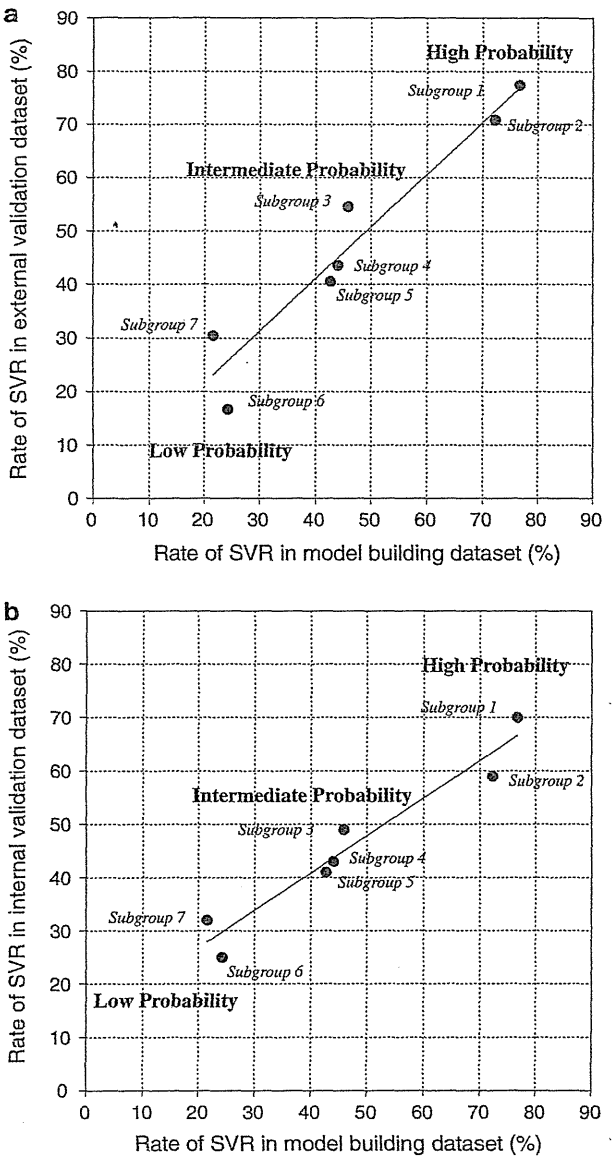

Fig. 2 Validation of the decision tree analysis by an internal and external validation dataset: subgroup-stratified comparison of the SVR rate. The rate of SVR in each subgroup was plotted. The *X* axis represents the model building, and the *Y* axis represents the validation datasets. **a** Internal validation and **b** external validation. There was a close correlation between the model building and the internal validation dataset (correlation coefficient $r^2 = 0.925$) and between the model building and the external validation dataset (correlation coefficient $r^2 = 0.936$)

original dataset used for model building. Each patient in the external validation set was allocated to subgroups 1–7 using the flow-chart form of the tree. The rates of SVR were 70% for subgroup 1, 59% for subgroup 2, 49% for subgroup 3, 43% for subgroup 4, 41% for subgroup 5, 25% for subgroup 6, and 32% for subgroup 7. The rates of SVR for each subgroup of patients were closely correlated

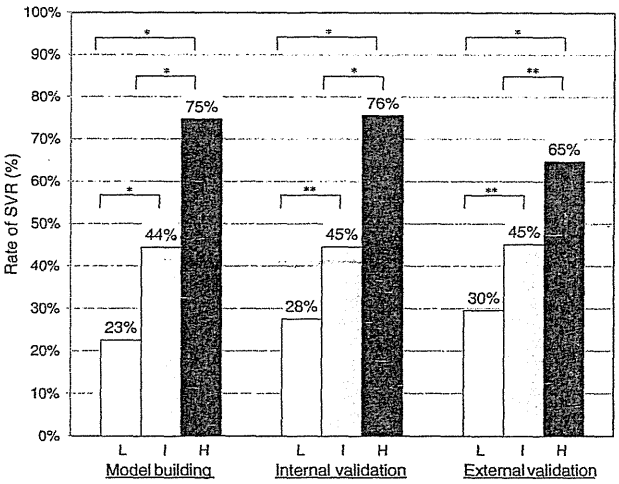

Fig. 3 Comparison of SVR rates between groups divided by the decision tree. The rate of SVR was compared among the 3 groups of patients divided by the decision tree analysis (*white*, *gray* and *black boxes*, indicating a low (*L*), intermediate (*I*) and high (*H*) probability group, respectively). The rate of SVR was significantly different among the 3 groups. $*p < 0.0001$, $**p < 0.001$

between the model-building dataset and the validation dataset ($r^2 = 0.936$) (Fig. 2b).

Construction of 3 groups according to the probability of SVR

Seven subgroups were reconstructed into 3 groups according to their predicted rates of SVR: the high probability group consisted of subgroups 1 and 2, the intermediate probability group consisted of subgroups 3, 4 and 5, and the low probability group consisted of subgroups 6 and 7. The rate of SVR was significantly different among the 3 groups (Fig. 3). The rate of SVR in the high probability group was consistently high: 75% for model building patients, 76% for internal validation patients and 65% for external validation patients. Conversely, the rate of SVR in the low probability group was consistently low: 23% for model building patients, 28% for internal validation patients and 30% for external validation patients. The rate of SVR in the intermediate probability group was 44% for model building patients, 45% for internal validation patients and 45% for external validation patients. Since 28–32% of patients were classified as high probability and 30–32% were classified as low probability, roughly 60% of patients were classified as having either a high or low probability of achieving SVR.

Effect of dose reductions of PEG-IFN and RBV on SVR

The cumulative dose of PEG-IFN and RBV was not included as a variable of analysis since the present study

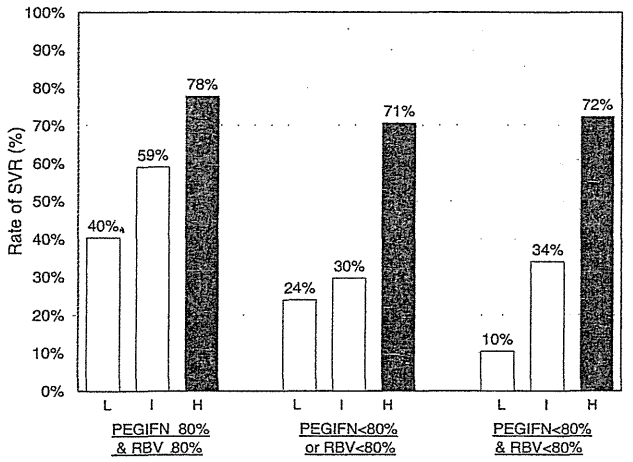

Fig. 4 Comparison of SVR rates among groups stratified by drug adherence. The 3 groups of patients divided by the decision tree analysis (*white*, *gray* and *black boxes* indicating a low (*L*), intermediate (*I*) and high (*H*) probability group, respectively) were further stratified according to the cumulative drug exposure of PEG-IFN and RBV. The good adherence group (≥80% planned dose of both PEG-IFN and RBV) had a higher rate of SVR compared with the poor adherence group (<80% planned dose of both PEG-IFN and RBV) in the low ($p = 0.0003$) and intermediate ($p = 0.007$) but not in the high probability group ($p = 0.53$)

aimed to develop a pre-treatment model for the prediction of response. To analyze the possible effect of drug reductions on the result of the decision tree analysis, 3 groups of patients divided by the decision tree analysis (low, intermediate and high probability group) were further stratified according to the cumulative drug exposure of PEG-IFN and RBV (Fig. 4). Even after adjustment for adherence, 3 groups of patients still had low, intermediate and high probability of achieving SVR, respectively. Of note, the good adherence group (≥80% planned dose of both PEG-IFN and RBV) had higher rates of SVR compared with the poor adherence group (<80% planned dose of both PEG-IFN and RBV) in the low ($p = 0.0003$) and intermediate ($p = 0.007$) probability group, but not in the high probability group ($p = 0.53$).

Factors associated with SVR by multivariate logistic regression analysis

We also explored the factors associated with SVR using a standard statistical analysis. By univariate analysis, age, gender, serum albumin, creatinine, alanine aminotransferase, GGT, red blood cell count, hemoglobin, hematocrit, platelet count and AFP were found to be associated with SVR (Table 2). HCVRNA load was not associated with SVR. By multivariate analysis, age, gender, GGT and platelet count were found to be independently associated with SVR (Table 3). Of note, AFP, which was selected as a significant predictor of response in the decision tree analysis, was not found to be an independent response predictor in the standard multivariate analysis. This indicates a unique feature of the decision tree analysis; i.e., it could identify significant predictors that specifically apply to selected patients, in this case patients younger than 50 years old.

Relationships between decision tree model and stage of fibrosis or HCV RNA load

Liver biopsy was performed in 664 patients. The distribution of fibrosis in three probability groups differed significantly. Advanced fibrosis (F3 or F4) was higher in the low probability group (39%) compared to the intermediate probability group (13%) ($p < 0.0001$) and to the high probability group (6%) ($p < 0.0001$). Advanced fibrosis was also higher in the intermediate group compared to the high probability group ($p = 0.01$). AFP was significantly associated with liver fibrosis stage: medians of AFP levels were 4.9, 5.9, 13.0 and 18.6 for F1, F2, F3 and F4, respectively ($p < 0.0001$, Spearman's rank correlations). Lower platelet counts correlated with advanced fibrosis stages (data not shown). The SVR rate was higher in the high probability group compared to the intermediate or low probability group after stratification by HCV RNA load. Among patients with low HCVRNA load (<400,000 IU/ml), the rate of SVR was 93, 59 and 50% for the high, intermediate and low probability group, respectively ($p = 0.002$ for high vs. intermediate and $p < 0.001$ for high vs. low probability groups). Among patients with a high HCVRNA load (≥400,000 IU/ml), the rate of SVR was 73, 42 and 21% for the high, intermediate and low probability group, respectively ($p < 0.001$ for high vs. low, high vs. intermediate and intermediate vs. low probability groups).

Discussion

Currently, the combination of PEG-IFN and RBV is the recommended therapy for chronic HCV infection. The rate of SVR with 48 weeks of therapy is around 50% in patients with HCV genotype 1b and a high HCV RNA titer [2, 3]. To date, the virological response during therapy is the most reliable means for predicting the likelihood of SVR [2, 24, 25]. More potent therapy, such as a triple combination of protease inhibitor, PEG-IFN and RBV, is being evaluated in clinical trials but is not readily available [26, 27]. Under the circumstances, pre-treatment prediction of the likelihood of SVR may be useful for both patients and physicians to support clinical decisions as to whether to start PEG-IFN/RBV therapy or delay treatment until a new more effective therapy becomes available.

Table 2 Comparison of pre-treatment factors between patients with and without sustained virological response (SVR) among the model building dataset ($n = 506$)

	SVR ($n = 240$)	Non-SVR ($n = 266$)	p
Age (years)	54 (25–75)	60 (36–73)	<0.0001
Male gender[a]	151/240 (63%)	171/266 (41%)	<0.0001
Body mass index (kg/m^2)	22.5 (16.8–32.0)	22.6 (15.5–33.3)	0.244
Albumin (g/dl)	4.1 (3.2–5.0)	4 (2.7–4.9)	0.004
Creatinine (mg/dl)	0.7 (0.44–1.14)	0.69 (0.39–1.47)	<0.0001
AST (IU/l)	59 (11–370)	61 (17–261)	0.457
ALT (IU/l)	58 (11–413)	53 (11–316)	0.031
GGT (IU/l)	31 (10–322)	43 (12–328)	0.005
Total cholesterol (mg/dl)	175 (87–297)	171 (73–274)	0.184
Triglyceride (mg/dl)	105 (36–474)	105 (33–294)	0.992
White blood cell count (/μl)	4,600 (2,200–10,900)	4,425 (1,800–10,810)	0.479
Neutrophils (/μl)	2,507 (667–7,870)	2,423 (900–7,281)	0.321
Red blood cell count (/μl)	455 (336–577)	441 (313–564)	0.001
Hemoglobin (g/dl)	14.3 (10.2–17.6)	13.9 (9.4–17.9)	0.004
Hematocrit (%)	42.1 (13.3–53.7)	41.2 (30.7–52.0)	0.031
Platelets (10^9/l)	178 (81–380)	142 (60–320)	<0.0001
AFP (ng/ml)	4.3 (0.9–680)	6.4 (1.9–468)	0.041
HCVRNA (10^3 IU/ml)	1,400 (100–5,100)	1,700 (100–5,100)	0.659
Fibrosis stage: F3–4[a]	21/198 (11%)	52/219 (24%)	<0.0001

Data expressed as median (range) unless otherwise indicated

AST aspartate aminotransferase, *ALT* alanine aminotransferase, *GGT* gamma-glutamyltransferase, *AFP* alpha-fetoprotein

[a] Data expressed as number/available data (percentage)

Table 3 Multivariate logistic regression analysis for factors associated with sustained virological response (SVR)

	Odds	95% CI	p value
Age (years)	0.96	0.94–0.98	0.001
Platelets (10^9/l)	1.09	1.04–1.14	<0.0001
ALT (IU/l)	1.01	1.00–1.01	0.001
GGT (IU/l)	0.99	0.98–0.99	<0.0001
Male gender	2.92	1.87–4.55	<0.0001

GGT gamma-glutamyltransferase

Using the data mining analysis, we constructed a simple decision tree model for the pre-treatment prediction of response to PEG-IFN/RBV. The analysis highlighted 5 variables relevant to response: age, gender, platelet count, AFP and GGT. Classification based on these variables identified subgroups of patients with high probabilities of achieving SVR among difficult to treat genotype 1b chronic hepatitis C patients. The reproducibility of the model was confirmed by the independent internal and external validation datasets. An advantage of the decision tree analysis over traditional regression models is that the decision tree model is user-intuitive and can be readily interpreted by medical professionals without any specific knowledge of statistics. Patients can be allocated to specific subgroups with a defined rate of response simply by following the flow-chart form. Using this model, an estimate of the response before treatment can be rapidly obtained, which may facilitate clinical decision making. Thus, this model could be readily applicable to clinical practice.

According to the results of the decision tree analysis, patients were categorized into 3 groups: the rate of SVR was 23–30% for the low probability group, 44–45% for the intermediate probability group and 65–76% for the high probability group. About 30% of patients were each categorized in the high and low probability group and the remaining 40% of patients in the intermediate probability group. These results support the evidence-based approach for selecting an optimum treatment strategy for individual patients. For example, patients in the high probability group may be the most suitable candidates for PEG-IFN/RBV therapy, while patients in the low probability group may be advised to wait for a future therapy, such as the combination of protease inhibitor, PEG-IFN and RBV. However, the estimation of low probability should not be used to preclude patients from therapy, and the final decision should be made on a case-by-case basis, taking into consideration the acceptance by the patient of a low likelihood of response and the potential risk of disease progression while waiting for a future therapy.

Another important finding was that poor adherence to drugs lowered the rate of SVR in the low and intermediate probability groups, which implies that effort should be made to maintain $\geq$80% of the planned dose of PEG-IFN and RBV in those patients. On the other hand, the rate of SVR was high irrespective of drug adherence in the high probability group. Whether shorter duration of therapy is sufficient in this group of patients should be confirmed in future study.

The variables used in the decision tree have been previously reported to associate with the efficacy of IFN therapy. Younger age and male gender are associated with a favorable response [28]. Lower platelet count is a hallmark of advanced fibrosis in chronic hepatitis C and is reported to be associated with poor response to IFN [29]. AFP is usually used for the screening or the diagnosis of hepatocellular carcinoma, but recent studies suggest an association between higher AFP levels and poor response to IFN therapy [30–33]. Previous report speculated that higher expression of AFP by hepatic progenitor cells may be associated with non-response to therapy [30]. Another report speculated that AFP levels predict poor response to therapy through the underlining link to advanced liver fibrosis [31]. Our data support the latter speculation since advanced fibrosis was associated with elevation of AFP levels. Fibrosis of the liver is an important predictor of response, but we did not include this factor in the decision tree analysis since liver biopsy may not always be available in general practice. As a result, two predictive factors that correlate with fibrosis stage (platelet counts and AFP) were selected in the model, and three probability groups reflected the different distribution of fibrosis stage. GGT is reported to be associated with insulin resistance and hepatic steatosis [34–37], a factor that confers resistance to IFN therapy [38–44]. What is unique to the present study is the visualization of response probability by combining these factors and its high reproducibility revealed by a high-quality validation of the model by internal and external validation datasets that were completely independent of the model building dataset. Since factors used in the model were clinical parameters that are readily available by the usual workup of patients, this model could be immediately applicable to clinical practice without imposing costs for additional examinations.

A potential limitation of this study is that data mining analysis has an intrinsic risk of showing relationships that fit to the original dataset but are not reproducible in different populations. Although internal and external validations showed that our model had high reproducibility, we recognize that further validation on a larger external validation cohort, especially in populations other than Japanese, may be necessary to further verify the reliability of our model.

In conclusion, we built a pre-treatment model for the prediction of virological response to PEG-IFN/RBV. Because this decision tree model was made up of simple variables, it can be easily applied to clinical practice. This model may have the potential to support decisions about patient selection for PEG-IFN/RBV based on a possibility of response weighed against the potential risk of adverse events or costs.

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Original Article

A predictive model of response to peginterferon ribavirin in chronic hepatitis C using classification and regression tree analysis

Masayuki Kurosaki,[1] Kotaro Matsunaga,[2] Itsuko Hirayama,[1] Tomohiro Tanaka,[1] Mitsuaki Sato,[1] Yutaka Yasui,[1] Nobuharu Tamaki,[1] Takanori Hosokawa,[1] Ken Ueda,[1] Kaoru Tsuchiya,[1] Hiroyuki Nakanishi,[1] Hiroki Ikeda,[1] Jun Itakura,[1] Yuka Takahashi,[1] Yasuhiro Asahina,[1] Megumu Higaki,[4] Nobuyuki Enomoto[3] and Namiki Izumi[1]

[1]Division of Gastroenterology and Hepatology and [2]Division of Pathology, Musashino Red Cross Hospital, Tokyo, [3]First Department of Internal Medicine, University of Yamanashi, Yamanashi, and [4]Department of Medical Science, Jikei Medical University, Tokyo, Japan

Aim: Early disappearance of serum hepatitis C virus (HCV) RNA is the prerequisite for achieving sustained virological response (SVR) in peg-interferon (PEG-IFN) plus ribavirin (RBV) therapy for chronic hepatitis C. This study aimed to develop a decision tree model for the pre-treatment prediction of response.

Methods: Genotype 1b chronic hepatitis C treated with PEG-IFN alpha-2b and RBV were studied. Predictive factors of rapid or complete early virological response (RVR/cEVR) were explored in 400 consecutive patients using a recursive partitioning analysis, referred to as classification and regression tree (CART) and validated.

Results: CART analysis identified hepatic steatosis (<30%) as the first predictor of response followed by low-density-lipoprotein cholesterol (LDL-C) (≥100 mg/dL), age (<50 and <60 years), blood sugar (<120 mg/dL), and gamma-glutamyltransferase (GGT) (<40 IU/L) and built decision tree model. The model consisted of seven groups with variable response rates from low (15%) to high (77%). The reproducibility of the model was confirmed by the independent validation group ($r^2 = 0.987$). When reconstructed into three groups, the rate of RVR/cEVR was 16% for low probability group, 46% for intermediate probability group and 75% for high probability group.

Conclusions: A decision tree model that includes hepatic steatosis, LDL-C, age, blood sugar, and GGT may be useful for the prediction of response before PEG-IFN plus RBV therapy, and has the potential to support clinical decisions in selecting patients for therapy and may provide a rationale for treating metabolic factors to improve the efficacy of antiviral therapy.

Key words: data mining, decision tree, HCV, low-density-lipoprotein-cholesterol, steatosis

INTRODUCTION

COMBINATION THERAPY WITH pegylated interferon (PEG-IFN) and ribavirin (RBV) is now recognized as a standard treatment for patients with chronic hepatitis C.[1] However, the rate of sustained virological response (SVR) to 48 weeks of PEG-IFN RBV combination therapy is only 50% in patients with hepatitis C virus (HCV) genotype 1b and high HCV RNA titer, so called difficult to treat chronic hepatitis C patients.[2,3] Within this difficult to treat group, the response to treatment sometimes can be highly heterogeneous for cases which are apparently equivalent in HCV RNA titer, making the prediction of response before treatment a difficult task. It has been suggested that early virological response (EVR), defined as either undetectable HCV RNA or a 2 log drop in HCV RNA at week 12, is a reliable means to predict SVR.[2,4] More recently, it has been suggested that patients with a rapid virological response (RVR: undetectable HCV RNA at week 4) and a complete EVR (cEVR: undetectable HCV RNA at week 12)

Correspondence: Dr Namiki Izumi, Division of Gastroenterology and Hepatology, Musashino Red Cross Hospital, 1-26-1 Kyonan-cho, Musashino-shi, Tokyo 180-8610, Japan. Email: nizumi@musashino.jrc.or.jp
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achieve high SVR rates, while patients with a partial EVR (pEVR: 2 log drop in HCV RNA but still detectable at week 12) have lower rates of SVR.[5] Since PEG-IFN RBV combination therapy is costly and accompanied by potential adverse effects, the ability to predict the possibility of RVR or cEVR before therapy and identifying curable patients may significantly influence the selection of patients for therapy. Moreover, identification of baseline predictors of poor response is particularly important to establish a rationale for identifying therapeutic targets to improve the efficacy of antiviral therapy.

Data mining is a method of predictive analysis which explores tremendous volumes of data to discover hidden patterns and relationships in highly complex datasets and enables the development of predictive models. The classification and regression tree (CART) analysis is a core component of the decision tree tool for data mining and predictive modeling,[6] is deployed to decision makers in various fields of business, and currently is being used in the area of biomedicine.[7–13] The results of CART analysis are presented as a decision tree, which is intuitive and facilitates the allocation of patients into subgroups by following the flow-chart form.[14] CART has been shown to be competitive with other traditional statistical techniques such as logistic regression analysis.[15]

In the present study, we used the CART analysis to explore baseline predictors of response to PEG-IFN plus RBV therapy among clinical, biochemical, virological and histological pretreatment variables and to define a pre-treatment algorithm to discriminate chronic hepatitis C patients who are likely to respond to PEG-IFN plus RBV therapy.

MATERIALS AND METHODS

Patients

A TOTAL OF 419 chronic hepatitis C patients were treated with PEG-IFN alpha-2b and RBV at Musashino Red Cross Hospital between December 2001 and December 2007. Among them, 400 patients who fulfilled the following inclusion criteria were enrolled in the present study. (i) infection by genotype 1b (ii) HCV RNA higher than 100 KIU/mL by quantitative PCR (Cobas Amplicor HCV Monitor, Roche Diagnostic systems, CA) which is usually used for the definition of high viral load in Japan (iii) lack of co-infection with hepatitis B virus or human immunodeficiency virus (iv) lack of other causes of liver disease such as autoimmune hepatitis, primary biliary cirrhosis, or alcohol intake of more than 20 g per day, and (v) having completed at least 12 weeks of therapy with an early virological response that could be evaluated. Patients received PEG-IFN alpha-2b (1.5 microgram/kg) subcutaneously every week and were administered a weight adjusted dose of RBV (600 mg for <60 kg, 800 mg for 60–80 kg, and 1000 mg for >80 kg) which is the recommended dosage in Japan. Data from two third of patients (269 patients) were used for the model building set and the remaining one third of patients (131 patients) were used as a validation set. Consent in writing was obtained from each patient and the study protocol conformed to the ethical guidelines of the 1975 Declaration of Helsinki and was approved by the institutional review committee.

Laboratory tests

Blood samples were obtained before therapy, and at least once every month during therapy and analyzed for hematologic tests, blood chemistries, and HCV RNA. In the present study, RVR and cEVR was defined as undetectable HCV RNA by qualitative PCR with a lower detection limit of 50 IU/mL (Amplicor, Roche Diagnostic systems, CA) at week 4 and 12, respectively. SVR was defined as undetectable HCV RNA at week 24 after the completion of therapy.

Histological examination

For all patients, liver biopsy specimens were obtained before therapy and were evaluated independently by three pathologists who were blinded to the clinical details. If there was a disagreement, the scores assigned by the majority of pathologists were used for the analysis. Fibrosis and activity were scored according to the METAVIR scoring system.[16] Fibrosis was staged on a scale of 0–4: F0 (no fibrosis), F1 (mild fibrosis: portal fibrosis without septa), F2 (moderate fibrosis: few septa), F3 (severe fibrosis: numerous septa without cirrhosis) and F4 (cirrhosis). Activity of necroinflammation was graded on a scale of 0–3: A0 (no activity), A1 (mild activity), A2 (moderate activity) and A3 (severe activity). Percentage of steatosis was quantified by determining the average proportion of hepatocytes affected by steatosis and graded on a scale of 0–3: grade 0 (no steatosis), grade 1 (0–9%), grade 2 (10–29%), and grade 3 (over 30%) as we reported previously.[17]

Database for analysis

A pretreatment database of 72 variables was created containing histological findings (grade of fibrosis, activity, and steatosis), laboratory tests including the quantity of HCV RNA by Cobas Amplicor, and clinical information (age, gender, body weight, and body mass index).

The baseline characteristics and test results are listed in Table 1. The overall rate of RVR/cEVR was 43% in the model building set and 48% in the validation set. There were no significant differences in the clinical backgrounds between these two groups. Hepatitis C viral mutations, such as mutations in interferon-sensitivity determining region or core amino acid residues 70 and 91, were not included in the present analysis. The dataset of laboratory tests was based on the digitized records in this hospital. Continuous data was split into categorized data by increment of 10; For example, age was categorized into <30, 30–39, 40–49, 50–59, 60–69, and ≥70.

Statistical analysis

Based on this database, the recursive partitioning analysis algorithm referred to as CART was implemented to define meaningful subgroups of patients with respect to the possibility of achieving RVR/cEVR. The CART belongs to a family of nonparametric regression methods based on binary recursive partitioning of data. The software automatically explore the data to search for optimal split variables, builds a decision tree structure and finally classifies all subjects into particular subgroups that are homogeneous with respect to the outcome of interest.[18] During the CART analysis, first, the entire study population, and thereafter, all newly defined subgroups, were investigated at every step of the analysis to determine which variable at what cut-off point yielded the most significant division into two prognostic subgroups that were as homogeneous as possible with respect to estimates of RVR/cEVR possibilities. This algorithm uses the impurity function (Gini criterion function) for splitting.[19] A restriction was imposed on the tree construction such that terminal subgroups resulting from any given split must have at least 20 patients. The CART procedure stopped when either no additional significant variable was detected or when the sample size was below 20. The resulting final subgroups were most homogeneous with respect to the probability of achieving RVR/cEVR. For this analysis, data mining software Clementine version 12.0 (SPSS Inc, Chicago, IL) was utilized. SPSS 15.0 (SPSS Inc, Chicago, IL) was used for logistic regression analysis.

RESULTS

Factors associated with RVR/cEVR by standard statistical analysis

WE FIRST ANALYZED 72 variables by univariate and multivariate logistic regression analysis to find factors associated with RVR/cEVR (Table 2). Patients with RVR/cEVR were significantly younger than those without. Among histological findings, grade of steatosis and stage of fibrosis was significantly lower in RVR/cEVR. Among hematologic tests, hemoglobin and hematcrit was significantly higher in RVR/cEVR. Among blood chemistry tests, creatinine and low-density lipoprotein cholesterol (LDL-C) was significantly higher and gamma-glutamyltransferase (GGT), low-density-lipoprotein cholesterol (LDL-C), and blood sugar were significantly lower in RVR/cEVR. The level of HCV RNA was significantly lower in RVR/cEVR. There were no significant differences in other tests.

Multivariate logistic regression analysis was performed on age, fibrosis stage, steatosis, HCVRNA, creatinine, hemoglobin, GGT, LDL-C, and blood sugar: hematcrit was not included since it is closely associated with hemoglobin. On multivariate analysis, age, grade of steatosis, level of HCV RNA, creatinine, hemoglobin, GGT, and LDL-cholesterol remained significant whereas stage of fibrosis, hemoglobin and blood sugar were not.

The CART analysis

The CART analysis was carried out on the model building set of 269 patients using the same variables as logistic regression analysis. Figure 1 shows the resulting decision tree. The CART analysis automatically selected five predictive variables to produce a total of seven subgroups of patients. The grade of steatosis was selected as the variable of initial split with an optimal cut-off of 30%. The possibility of achieving RVR/cEVR was only 18% for patients with hepatic steatosis of 30% or more compared to 47% for patients with hepatic steatosis of less than 30%. Among patients with hepatic steatosis of less than 30%, the level of serum LDL-C, with an optimal cut-off of 100 mg/dL, was selected as the variable of second split. Patients with higher LDL-C level had the higher probability of RVR/cEVR (57% vs. 32%). Among patients with LDL-C of less than 100 mg/dL, age, with an optimal cut-off of 60, was selected as the third variable of split. Younger patients had the higher probability of RVR/cEVR (49% vs. 15%). Among patients younger than 60, the blood sugar, with an optimal cut-off of 120 mg/dL, was selected as the forth variable of split. Patients with lower blood sugar level had the higher probability of RVR/cEVR (71% vs. 31%). Among patients with hepatic steatosis of less than 30% and LDL-C of 100 mg/dL or more, age, with an optimal cut-off of 50, was selected as the third variable of split, younger being the predictor of higher RVR/cEVR probability (77% vs. 50%). Among patients older than 50,

Table 1 Clinical characteristics of patients

	Model set $n = 269$	Validation set $n = 131$	*P*-value
Sex (M/F)	127/142	55/76	0.325
Age (years)	57.7 ± 10.1	57.6 ± 10.0	0.932
Body weight (kg)	59.6 ± 11.0	57.5 ± 9.5	0.094
Body mass index (kg/m^2)	23.2 ± 3.1	23.3 ± 3.8	0.934
Total protein (g/dL)	7.6 ± 0.5	7.7 ± 0.6	0.558
Albumin (g/dL)	4.2 ± 0.3	4.2 ± 0.3	0.349
Globulin (g/dL)	3.4 ± 0.5	3.4 ± 0.6	0.989
Aspartate aminotransferase (IU/L)	58.1 ± 43.1	55.8 ± 37.5	0.601
Alanine aminotransferase (IU/L)	70.9 ± 49.2	66.4 ± 52.6	0.462
Gamma-glutamyltransferase (IU/L)	49.6 ± 44.0	45.2 ± 34.4	0.33
Lactate dehydrogenase (IU/L)	289.3 ± 112.3	301.5 ± 109.3	0.417
Total bilirubin (mg/dL)	0.71 ± 0.28	0.69 ± 0.23	0.317
Direct bilirubin (mg/dL)	0.23 ± 0.12	0.25 ± 0.10	0.147
Indirect bilirubin (mg/dL)	0.48 ± 0.21	0.44 ± 0.16	0.064
Alkaline phosphatase (IU/L)	290.9 ± 107.6	292.5 ± 107.6	0.917
Leucine aminopeptidase (IU/L)	64.3 ± 14.3	65.5 ± 12.3	0.543
Thymol turbidity test (KU)	7.1 ± 3.4	8.0 ± 3.7	0.062
Zinc sulfate turbidity test (KU)	15.4 ± 4.9	16.3 ± 5.4	0.188
Choline esterase (IU/L)	318.1 ± 81.7	321.1 ± 78.1	0.798
Ammonia (microg/dL)	39.7 ± 20.2	45.0 ± 15.6	0.668
Blood sugar (mg/dL)	125.9 ± 41.1	117.4 ± 47.9	0.081
Glycohemoglobin (%)	5.6 ± 1.6	5.4 ± 1.2	0.797
Total cholesterol (mg/dL)	170.8 ± 33.9	175.6 ± 36.8	0.170
Low-density-lipoprotein-cholesterol (mg/dL)	96.5 ± 25.2	100.9 ± 28.5	0.153
High-density-lipoprotein-cholesterol (mg/dL)	54.2 ± 15.9	55.2 ± 17.4	0.612
Triglyceride (mg/dL)	108.5 ± 47.8	102.8 ± 46.4	0.306
Creatinine (mg/dL)	0.72 ± 0.15	0.74 ± 0.17	0.236
Urea nitrogen (mg/dL)	14.1 ± 3.4	14.9 ± 3.9	0.123
Uric acid (mg/dL)	5.3 ± 1.2	5.2 ± 1.2	0.715
Sodium (mEq/L)	142.2 ± 2.0	142.4 ± 2.0	0.471
Potassium (mEq/L)	4.3 ± 0.3	4.3 ± 0.4	0.578
Chloride (mEq/L)	104.0 ± 2.2	104.0 ± 2.6	0.905
Calcium (mg/dL)	9.1 ± 0.4	9.2 ± 0.4	0.479
Phosphorus (mg/dL)	3.5 ± 0.5	3.5 ± 0.6	0.814
Magnesium (mg/dL)	2.2 ± 0.2	2.3 ± 0.3	0.390
Amylase (IU/L)	178.7 ± 125.8	175.1 ± 133.1	0.118
Creatine kinase (IU/L)	114.9 ± 147.6	119.3 ± 73.7	0.849
Iron (microg/dL)	104.7 ± 53.2	109 ± 37	0.726
Ferritin (ng/mL)	111.3 ± 103.3	59.7 ± 118.5	0.405
C-reactive peptide (mg/dL)	0.2 ± 1.1	0.1 ± 0.1	0.586
Immunoglobulin G (mg/dL)	1849 ± 426	1988 ± 525	0.129
Immunoglobulin M (mg/dL)	141 ± 69	205 ± 106	0.200
Immunoglobulin A (mg/dL)	323 ± 675	291 ± 81	0.784
Triiodothyronine (pg/mL)	2.3 ± 0.3	2.2 ± 0.3	0.358
Thyroxin (ng/dL)	0.9 ± 0.1	0.9 ± 0.1	0.872
Thyroid stimulating hormone (micro IU/mL)	1.8 ± 1.4	1.7 ± 0.7	0.939
White blood cell count (/microl)	5243 ± 1591	5286 ± 1101	0.843
Segmented neutrophils (%)	55.4 ± 10.8	57.0 ± 10.0	0.297
Band neutrophils (%)	1.5 ± 1.6	0.5 ± 0.6	0.250
Eosinophils (%)	2.9 ± 2.3	2.4 ± 1.4	0.127

Table 1 *Continued*

	Model set $n = 269$	Validation set $n = 131$	*P*-value
Basophiles (%)	0.6 ± 0.4	0.6 ± 0.3	0.727
Lymphocytes (%)	34.6 ± 9.6	34.0 ± 9.3	0.682
Monocytes (%)	6.6 ± 2.2	6.2 ± 2.6	0.149
Red blood cell count (10^4/microl)	458 ± 43	455 ± 47	0.643
Hemoglobin (g/dL)	14.4 ± 1.5	14.5 ± 1.5	0.618
Hematcrit (%)	42.7 ± 4.0	42.9 ± 4.4	0.717
Reticulocytes (%)	1.4 ± 0.4	1.4 ± 0.4	0.762
Mean corpuscular volume (fL)	93.3 ± 4.5	93.8 ± 5.41	0.466
Mean corpuscular hemoglobin concentration (pg)	31.5 ± 1.9	31.7 ± 2.3	0.583
Mean corpuscular hemoglobin concentration (g/dL)	33.8 ± 0.9	33.7 ± 1.3	0.910
Platelets (10^4/microl)	16.8 ± 5.4	16.3 ± 4.5	0.480
Prothrombin time (s)	11.7 ± 1.2	11.7 ± 0.9	0.762
Prothrombin time (activity %)	104.6 ± 14.4	102.6 ± 14.8	0.363
Prothrombin time (international normalized ratio)	1.0 ± 0.1	1.0 ± 0.1	0.387
Thrombin time (%)	97.2 ± 31.3	109 ± 31.5	0.231
Activated partial thromboplastin time (s)	29.7 ± 4.4	29.1 ± 2.7	0.260
Hepaplastin test (%)	97.8 ± 20.3	95.4 ± 19.4	0.523
Fibrinogen (%)	237 ± 44	225 ± 45	0.069
Hepatitis C virus RNA (<850/≥850 KIU/mL)	130/139	70/61	0.394
Histological grade of			
Activity (A1/A2/A3)	138/107/24	62/55/14	0.714
Fibrosis (F1/F2/F3/F4)	135/74/57/3	58/40/27/6	0.131
Steatosis (0%/1–9%/10–29%/30%≦)	89/109/37/34	49/45/21/16	0.643
Hepatitis C virus RNA negative at week 12 (yes/no)	116/153	63/68	0.349

the level of GGT, with an optimal cutoff of 40 U/L, were then selected as the fourth level of split, low levels being the predictor of higher RVR/cEVR probability (60% vs. 35%).

All five factors selected as significant variables in the CART analysis were also significantly associated with RVR/cEVR by univariate analysis (Table 2). In addition, steatosis, LDL-C, age and GGT were also independently

Table 2 Factors associated with rapid or complete early virological response by univariate and multivariate logistic regression analysis

Parameter	Category	Univariate			Multivariate		
		Odds	95% CI	*P*-value	Odds	95% CI	*P*-value
Age (years)	<50 vs. ≥50	2.65	1.51–4.65	<0.001	2.03	1.04–3.97	0.039
Fibrosis stage	F1-2 vs. F3-4	2.47	1.31–4.66	0.005	1.77	0.85–3.68	0.120
Steatosis (%)	<30 vs. ≥30	4.11	1.64–10.29	0.003	2.88	1.07–7.79	0.037
Hepatitis C virus RNA (KIU/mL)	<850 vs. ≥850	1.97	1.21–3.22	0.007	1.93	1.09–3.43	0.025
Creatinine (mg/dL)	≥0.8 vs. <0.8	3.30	1.96–5.56	<0.001	3.54	1.88–6.67	<0.001
Hemoglobin (g/dL)	≥14.5 vs. <14.5	1.76	1.08–2.87	0.023	1.38	0.74–2.57	0.320
Hematcrit (%)	≥43 vs. <43	1.75	1.07–2.84	0.003			
Gamma-glutamyltransferase (IU/L)	<40 vs. ≥40	2.06	1.26–3.37	0.004	2.45	1.32–4.56	0.005
Low-density-lipid cholesterol (mg/dL)	≥100 vs. <100	2.71	1.61–4.55	<0.001	2.21	1.21–4.06	0.010
Blood sugar (mg/dL)	<120 vs. ≥120	2.00	1.02–3.95	0.045	1.42	0.64–3.13	0.390

CI, confidence interval.

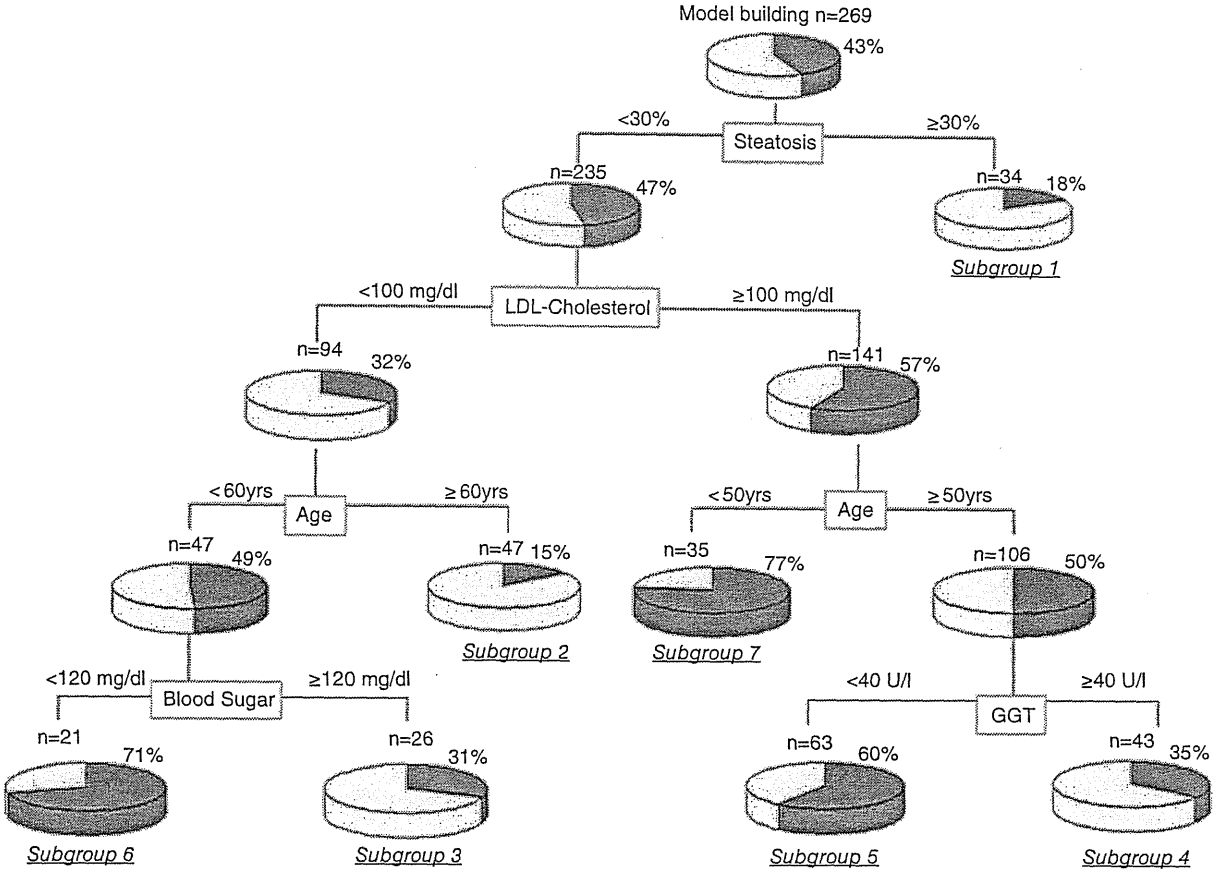

Figure 1 Classification and regression tree analysis. Boxes indicate the factors used for splitting and the cut-off value for the split. Pie charts indicate the rate of RVR/cEVR for each group of patients after splitting. Terminal subgroups of patients discriminated by the analysis are numbered from one to seven. GGT, gamma-glutamyltransferase; LDL, low-density-lipoprotein.

associated with RVR/cEVR by multivariate logistic regression analysis while blood sugar was not (Table 2). On the other hand, HCVRNA and creatinine which were significantly associated with RVR/cEVR by multivariate analysis were not selected as significant variables in CART analysis.

The probabilities of RVR/cEVR for the seven subgroups derived by this process were highly variable. The subgroup whose hepatic steatosis was less than 30%, serum LDL-C was 100 mg/dL or more and of an age less than 50 years (subgroup 7) showed the highest probability of RVR/cEVR (77%), while the subgroup whose hepatic steatosis more than 30% (subgroup 1) and the subgroup whose hepatic steatosis was less than 30% but serum LDL-C was less than 100 mg/dL and of an age greater than 60 years (subgroup 2) showed the lowest probability of RVR/cEVR (18% and 15%, respectively).

Validation of the CART analysis

The results of the CART analysis were validated with a validation dataset of 131 cases which is independent of the model building dataset. Each patient in the validation set was allocated to subgroups 1–7 using the flowchart form of the CART tree. The rates of RVR/cEVR were 20% for subgroups 1 and 2, 29% for subgroups 3, 38% for subgroup 4, 59% for subgroup 5, 71% for subgroup 6, and 85% for subgroups 7. The rates of RVR/cEVR for each subgroup of patients were closely correlated between the model building dataset and the validation dataset (Fig. 2).

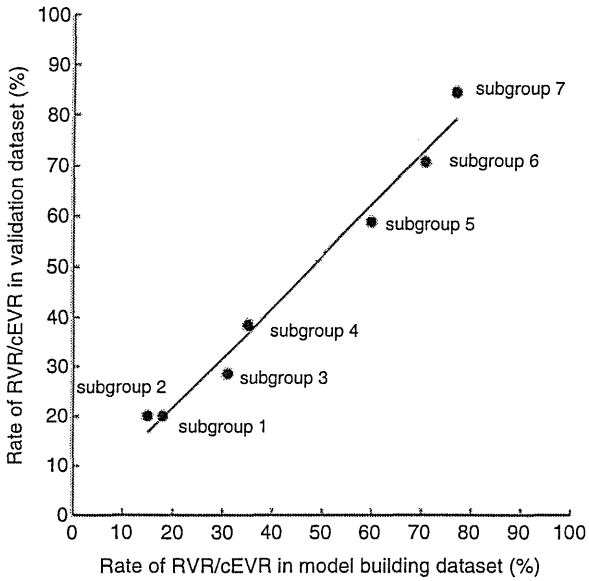

Figure 2 Validation of the classification and regression tree (CART) analysis: Subgroup stratified comparison of the rate of rapid or complete early virological response (RVR/cEVR) between the model building and validation datasets. Each patient in the validation set was allocated to subgroups 1–7 by following the flow-chart form of the CART tree and the rates of RVR/cEVR were calculated. The rate of RVR/cEVR in each subgroup was plotted. The *x*-axis represents the rate of RVR/cEVR in the model building datasets and the y-axis represents the rate of RVR/cEVR in the validation datasets. The rates of achieving RVR/cEVR in each subgroup of patients closely correlated between the model building dataset and the validation dataset ($r^2 = 0.987$).

Construction of 3 groups according to the probability of RVR/cEVR

If the seven subgroups were reconstructed into three groups according to their rate of RVR/cEVR, the rate of RVR/cEVR was 16% for low probability group (subgroup 1 and 2), 46% for intermediate probability group (subgroup 3, 4, and 5) and 75% for high probability group (subgroup 6 and 7; $P < 0.0001$).

Effect of adherence

Adherence of PEG-IFN and RBV was not included as a variable of analysis since the present study aimed to develop a pre-treatment model for the prediction of response. To analyze the possible effect of adherence on the result of CART analysis, three groups of patients divided by CART (low, intermediate and high probability group) were further stratified according to adherence of PEG-IFN and RBV. Poor adherence was defined as taking less than 80% planned dose of PEG-IFN or RBV at 12 weeks, and good adherence was defined as taking more than 80% planned dose of both PEG-IFN and RBV at 12 weeks. The result is shown in Figure 3. Among patients with good adherence, the rate of RVR/cEVR was 19% for low probability group, 52% for intermediate probability group and 77% for high probability group. Among poor adherence group, the rate of RVR/cEVR was 13% for low probability group, 41% for intermediate probability group and 73% for high probability group. Collectively, even after adjustment for adherence, 3 groups of patients divided by CART analysis still had low, intermediate and high probability of achieving RVR/cEVR, respectively.

DISCUSSION

IN THE PRESENT study, we performed the CART analysis and built a simple decision tree model for the pre-treatment prediction of response to PEG-IFN plus

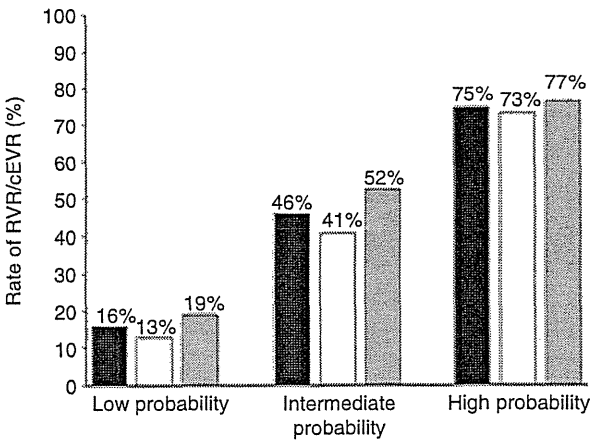

Figure 3 The rate of rapid or complete early virological response (RVR/cEVR) between the classification and regression tree (CART) groups stratified by adherence. The three groups of patients divided by CART (low, intermediate and high probability group) were further stratified according to adherence of peg-interferon (PEG-IFN) plus ribavirin (RBV). Black, white and gray boxes in the bar chart indicate total patients, patients with poor adherence (taking less than 80% planned dose of PEG-IFN or RBV at 12 weeks), and good adherence (taking more than 80% planned dose of both PEG-IFN and RBV at 12 weeks), respectively. Even after adjustment for adherence, 3 groups of patients divided by CART analysis still had low, intermediate and high probability of achieving RVR/cEVR, respectively.

RBV therapy. The analysis highlighted five host variables relevant to response: steatosis, LDL-C, age, blood sugar and GGT. Classification of patients based on these variables identified subgroups of patients with high probabilities of achieving RVR/cEVR among difficult to treat chronic hepatitis C patients. The reproducibility of the model was confirmed by the independent validation datasets. According to the result of the CART, patients were categorized into 3 groups: the rate of RVR/cEVR was 16% for low probability group, 46% for intermediate probability group and 75% for high probability group. The result of the CART analysis could be readily applicable to clinical practice because patients could be allocated to specific subgroups with a defined rate of response simply by following the flow-chart form. Although an early disappearance of serum HCV RNA is the prerequisite for achieving SVR, no reliable baseline predictors of response to PEG-IFN plus RBV therapy are established to date. Thus, this model may have the potential to support decisions in patient selection for PEG-IFN plus RBV therapy or to tailor treatment strategies for individual patients. Moreover, our result may provide a rationale for treating metabolic factors to improve the efficacy of antiviral therapy.

Among variables relevant to the prediction of RVR/cEVR, the grade of hepatic steatosis was selected as the variable of the first split. Previous studies suggested that steatosis induces resistance to IFN and RBV combination therapy[20,21] along with underlining metabolic factors such as insulin resistance or obesity.[21–24] In the present study, the grade of steatosis correlated positively with BMI and serum glucose level (data not shown) suggesting the etiologic role of metabolic factors. In addition, serum glucose level was selected as a predictor of RVR/cEVR at the fourth level of split. Serum GGT, which is associated with obesity,[25] insulin resistance[26] and response to IFN therapy,[27–30] was also selected as a predictor of RVR/cEVR at fourth level of splitting which may emphasize the importance of metabolic factors in therapeutic resistance. These findings raise the possibility that treatment of these metabolic factors may improve the virological response to the PEG-IFN plus RBV therapy. This hypothesis should be examined by a prospective study.

We and others have reported that steatosis, obesity and insulin resistance are associated with the progression of fibrosis,[17,31–33] which can interfere indirectly with the effect of IFN on hepatocytes. Other possible mechanisms of resistance by steatosis or metabolic factors include dysregulation of adipocytokines[34] or oxidative stress which may inhibit intracellular IFN signaling pathway.[35] Despite these findings, the precise mechanism of resistance is not established and further investigation is needed.

Another factor relevant in the prediction of RVR/cEVR was LDL-C. LDL-C was selected as the second factor for splitting by CART, and was an independent predictor of RVR/cEVR by logistic regression analysis. LDL-C recently has attracted attention as a novel predictor of response to IFN or PEG-IFN plus RBV.[30,36,37] Since *in vitro* study showed that LDL-C receptor acts as a receptor for HCV and LDL-C competitively inhibit the binding of HCV,[38] high level of serum LDL-C may inhibit HCV entry to hepatocytes and attenuate replication. LDL-C and its receptor may be a future therapeutic target.

Not all factors selected as significant variables in the CART analysis were also significantly associated with response by standard statistical analysis: blood sugar was associated with response by univariate analysis but not by multivariate logistic regression analysis On the other hand, HCVRNA and creatinine which were significantly associated with RVR/cEVR by multivariate analysis were not selected as significant variables in CART analysis. These differences may indicate both the unique feature and the limitations of the CART analysis. To note, blood sugar was significantly associated with RVR/cEVR within specialized subgroups of patients defined by the CART analysis: in subgroup of patients with steatosis <30%, LDL-C <100 mg/dL and younger than 60, which indicate the unique feature of the CART analysis that it could visualize significant predictors that specifically apply to selected patients. The limitation is that not all significant factors may be adopted in the decision tree since we applied the rule to stop CART procedure when the sample size was below 20. This rule was applied to avoid the generation of over-fit model which may lack universality. Therefore, it is possible that HCVRNA or creatinine may become a significant variable in the CART analysis if larger number of patients were included in the analysis. Stage of fibrosis was significantly associated with response to therapy by univariate analysis but not by multivariate analysis and not selected as a significant variable in the CART analysis. The possible reason is that advanced fibrosis is associated with older age as a confounding factor.

CART analyses are gaining acceptance in medical research in addition to biomedical field. Recent publications include the prediction of aggressive prostate cancer,[8] diabetic vascular complications,[19] prognosis of melanoma,[7,39] response to preoperative radiotherapy for rectal tumor,[9] prognostic groups in colorectal carcinoma,[12] and outcome after liver failure.[11] An advantage

of CART over traditional regression models is that it can identify prognostic subgroups that are useful in clinical practice. Because the results of CART analysis are presented as a decision tree, which is intuitive, they can be readily interpreted by medical professionals without any specific knowledge of statistics. The most important consideration is that five variables used in the decision tree were clinical parameters that are readily available by the usual work-up of patients before therapy. Especially, glucose, GGT and LDL-C are simple biochemical markers that are easily measured at a low cost. Using this model, we can rapidly develop an estimate of the response before treatment, which may facilitate clinical decision making.

In conclusion, we built a pre-treatment model for the prediction of virological response in PEG-IFN plus RBV therapy. Because this decision tree model was made up of simple host factors such as steatosis, LDL-C, age, blood sugar and GGT, it can be easily applied to clinical practice. This model may have the potential to support decisions in patient selection for PEG-IFN plus RBV therapy based on the possibility of response against a potential risk of adverse events or costs, and may provide a rationale for treating metabolic factors to improve the efficacy of antiviral therapy.

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Reproducibility and usability of chronic virus infection model using agent-based simulation; comparing with a mathematical model

Jun Itakura[a,*], Masayuki Kurosaki[a], Yoshie Itakura[a], Sinya Maekawa[b], Yasuhiro Asahina[a], Namiki Izumi[a], Nobuyuki Enomoto[b]

[a] Division of Gastroenterology and Hepatology, Musashino Red Cross Hospital, 1-26-1 Kyonan-cho, Musashino-shi, Tokyo 180-8610, Japan

[b] First Department of Internal Medicine, Faculty of Medicine, University of Yamanashi, 1110, Shimogatou, Chuou-shi, Yamanashi 409-3898, Japan

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ABSTRACT

We created agent-based models that visually simulate conditions of chronic viral infections using two software. The results from two models were consistent, when they have same parameters during the actual simulation. The simulation results comprise a transient phase and an equilibrium phase, and unlike the mathematical model, virus count transit smoothly to the equilibrium phase without overshooting which correlates with actual biology in vivo of certain viruses. We investigated the effects caused by varying all the parameters included in concept; increasing virus lifespan, uninfected cell lifespan, uninfected cell regeneration rate, virus production count from infected cells, and infection rate had positive effects to the virus count during the equilibrium period, whereas increasing the latent period, the lifespan-shortening ratio for infected cells, and the cell cycle speed had negative effects. Virus count at the start did not influence the equilibrium conditions, but it influenced the infection development rate. The space size had no intrinsic effect on the equilibrium period, but virus count maximized when the virus moving speed was twice the space size. These agent-based simulation models reproducibly provide a visual representation of the disease, and enable a simulation that encompasses parameters those are difficult to account for in a mathematical model.

1. Introduction

All viruses need hosts as a basis for their life. When a virus enters the host body, it invades cells and uses both its own enzymes and those of the host cells to replicate. Host cells infected by viruses launch a self-defense system known as the innate immune system (See and Wark, 2008; Naniche, 2009), which inhibits viral replication and uses the human leukocyte antigen system and cytokines to elicit an immune response. Immune cells that have received signals from host cells activate other immune cells, neutralize viruses in the serum by means of antibodies, and prevent the virus from replicating and proliferating by destroying or curing host cells. Viral infection is a disorder based on the interactions between viruses and cells.

The power relationship between these agents changes along with the progression of the disease. In the very early stages of infection, as the host defense mechanisms are immature, the virus has the ability to overwhelm the host cells, actively replicate, and proliferate. Subsequently, as the capacity of the immune system improves, the speed of viral proliferation drops and the virus count reaches a peak. Infected host cells begin to be disrupted by the immune system or virus particles, and symptoms appear as a result. If the immune system is stronger than the virus, then the viral counts decline, and, in transient viral disorders, the virus is finally eliminated and the host recovers. In chronic viral disorders, however, the power relationship between the virus and host cells reaches equilibrium, and a long-term power balance is maintained with the virus count reaching a plateau.

Mathematical models have been proposed to study the dynamics of such viral disorders, and are regarded as being of value in understanding this phenomenon (Ho et al., 1995; Nowak et al., 1996; Neumann et al., 1998). However, these models are difficult to understand for clinicians, and their applicability is somewhat limited in everyday practice. In clinical research, measurements of viral dynamics in patients for short duration have been made for human

Abbreviations: HIV, human immunodeficiency virus; HBV, hepatitis B virus; HCV, hepatitis C virus.

* Corresponding author. Tel.: +81 422 32 3111; fax: +81 422 32 9551.
E-mail address: jitakura@musashino.jrc.or.jp (J. Itakura).

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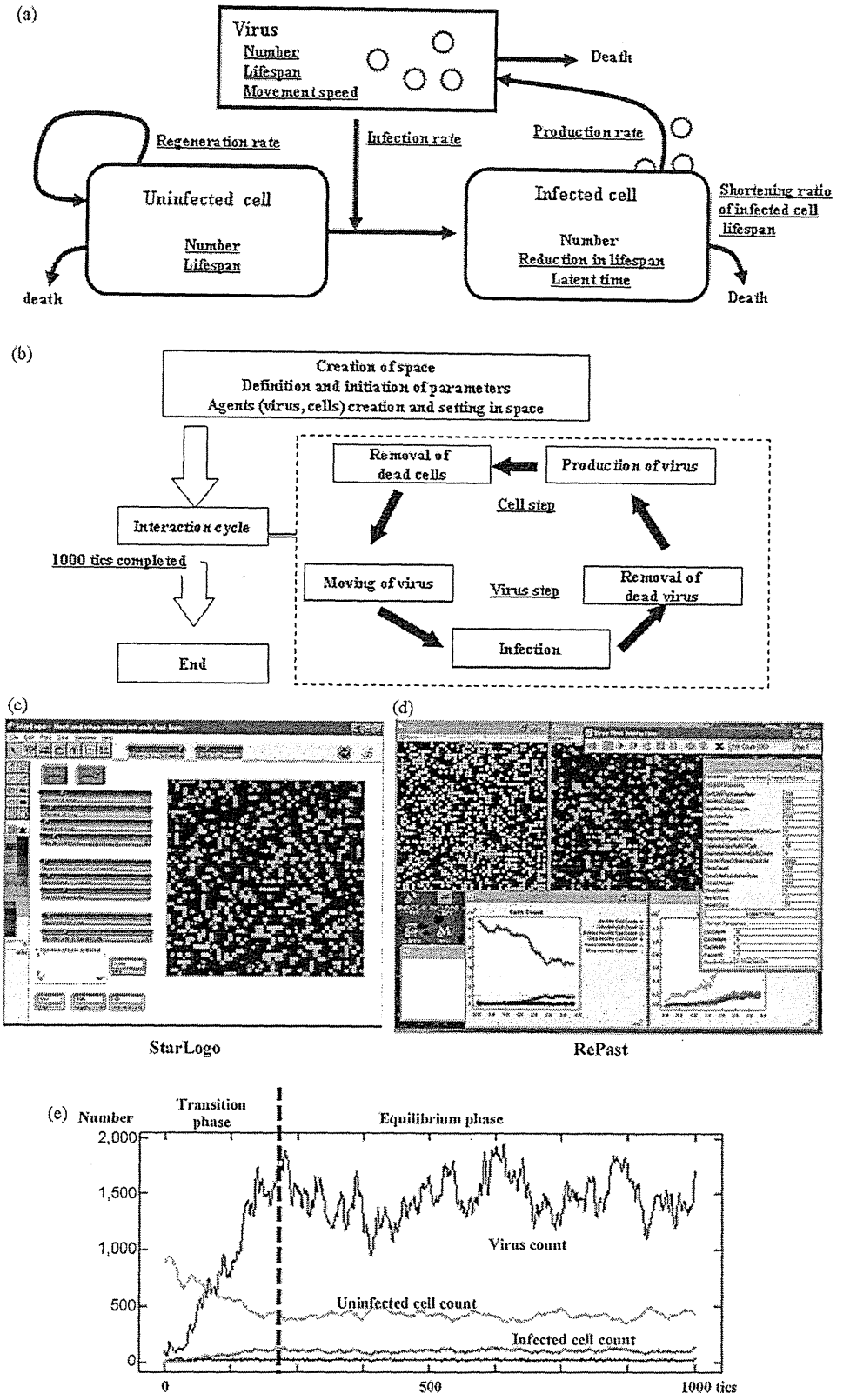

Fig. 1. Simulation design and an example of simulation results. (a) Model concept. Viruses, uninfected cells, and infected cells were treated as agents, and parameters were set for each of these and for interactions between agents (underlined). (b) Flowchart of the program. After preparing the simulation, we entered the interaction cycle, in which virus steps (such as movement) and cell steps were repeated. One cycle was counted as 1 tic, and the simulation concluded after 1000 tics. (c and d) Simulation screen using (c) StarLogo and (d) RePast. Yellow circles are viruses, green squares are uninfected cells, and orange and red indicate infected cells, with orange indicating the latent period. In StarLogo, all the agents are shown on the same screen, but in RePast, viruses and cells are shown in separate windows. (e) Example of a simulation chart in StarLogo. After the start of simulation the virus count and infected cell count increase while the uninfected cell count decreases, with equilibrium state reached after a certain number of tics.