

# Statistical analysis in risk assessment of chemicals

Takayuki Fujii(\*1), Masayuki Kageyama(\*1), Masashi Gamou(\*2), Koji Kanefuji(\*1), and Hiroe Tsubaki(\*1)

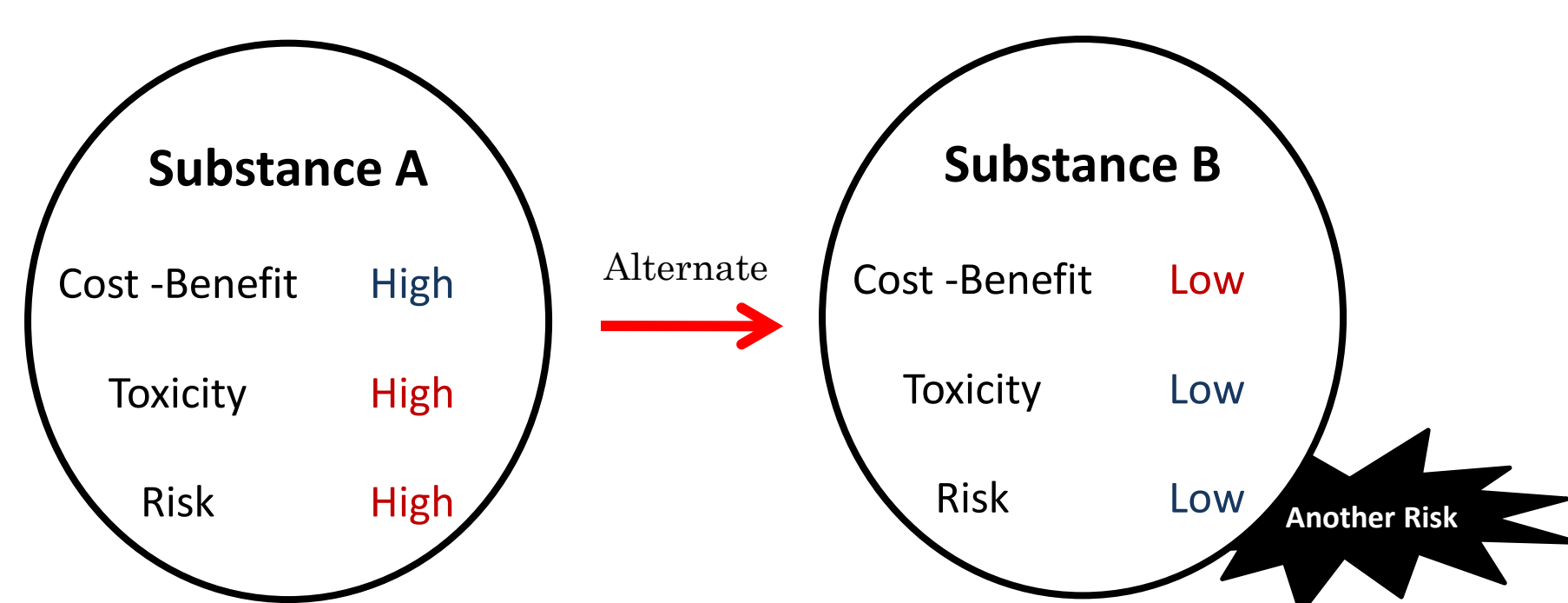
\*1:The institute of statistical mathematics \*2:National Institute of Advanced Industrial Science and Technology

## OUTLINE

Our aim is to construct a statistical model and the inference algorithm that provide a theoretical proof for the risk assessment of chemicals. In this talk, we introduce a graphical modeling that is suitable for the representation of the causal relations with uncertainty. It becomes better combining existing statistical tools such as EM-algorithm, latent variables and so on. Our approach is challenging, but substantial progress can be made.

## Risk Trade-off of Chemicals

Once we find toxicity of the substance A, ....



Another risk may offset the reduction in the target risk

### Risk Trade-Off

In order to promote appropriate assessment and management of chemical risks, it is necessary to construct the evaluation system which makes it possible to quantify and compare the risk of the substance and its alternative.

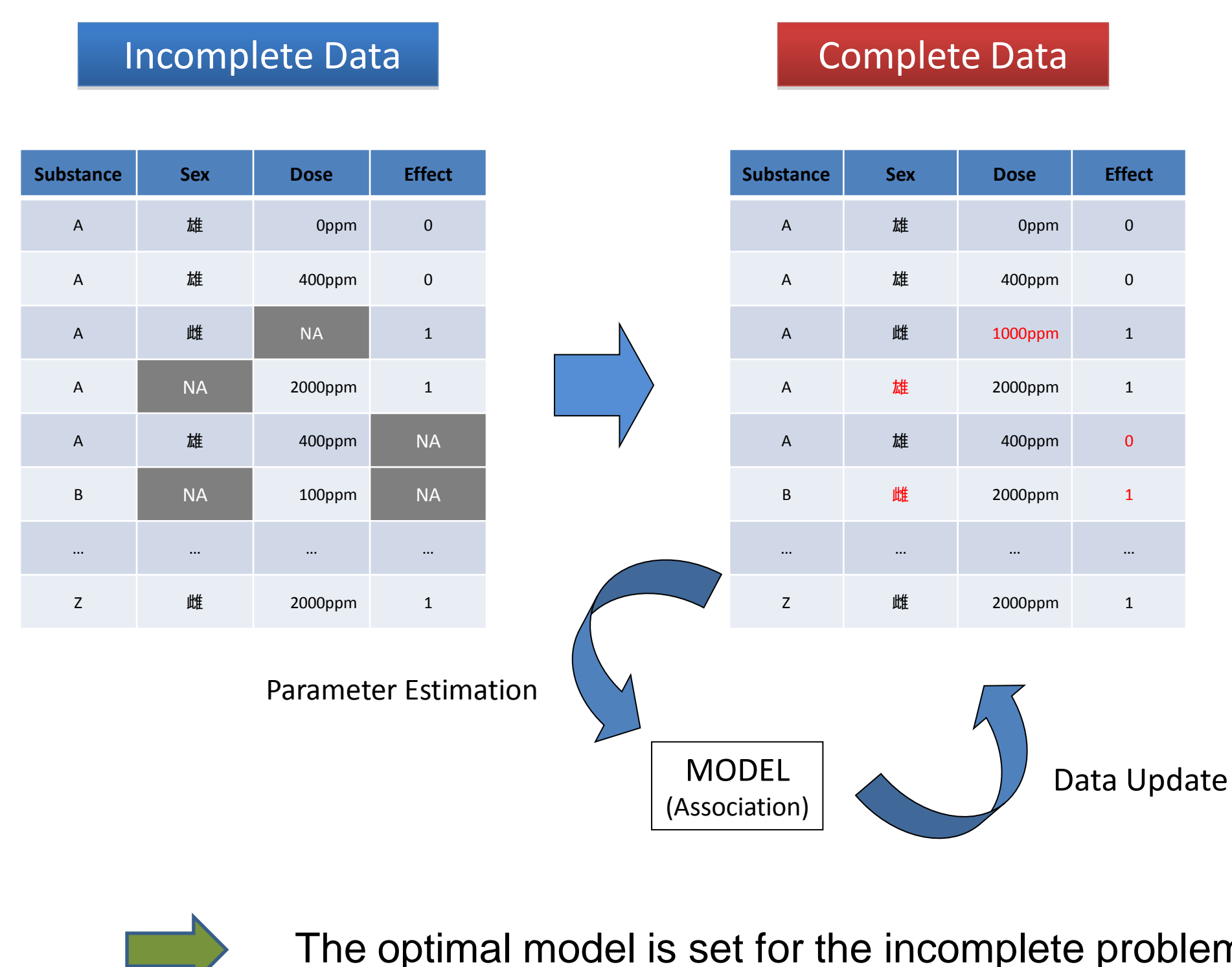
## Statistical Tools

We use a graphical model to describe the relativity among the markers.

### Extensions

EM algorithm is a technique for analysing the data with missing value.

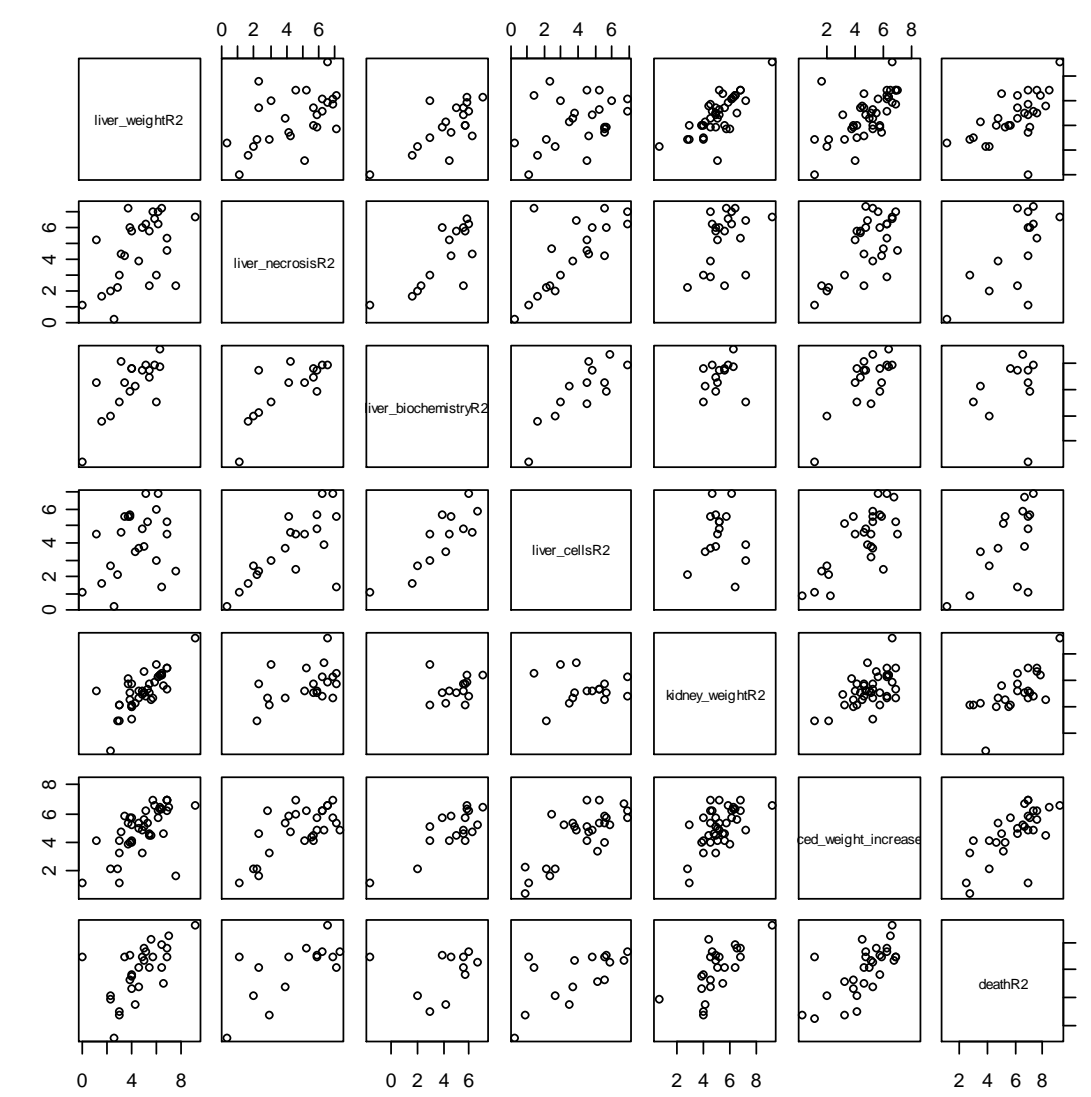
## EM Algorithm



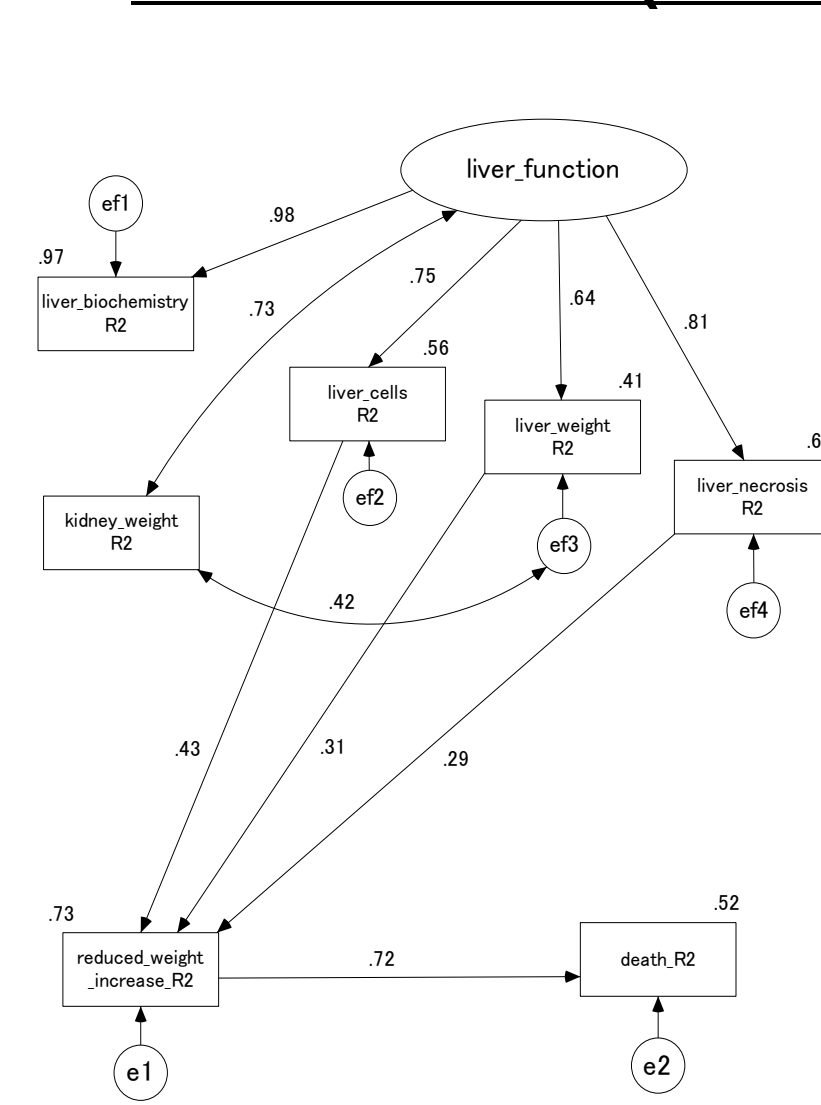
## Results

The followings are some analytical Results for the chemical toxicity effect of liver and Kidney by rat's oral ingestion.

### 1. Scatter Plot



### 2. Latent Model (AIC=58.453)



Pass-Coefficient				
	MLE	S.D.	Test Statistics	Prob.
Liver_neuro_R2 <-> Liver function	1.559	.262	5.947	***
Liver_cellR2 <-> Liver function	1.303	.249	5.242	***
Liver_weightR2 <-> Liver function	1.109	.229	4.849	***
Weight_Inc_R2 <-> Liver_cellR2	.422	.123	3.417	***
Weight_Inc_R2 <-> Liver_weightR2	.303	.106	2.849	.004
Weight_Inc_R2 <-> Liver_neuro_R2	.259	.120	2.158	.031
Liver_bioc_R2 <-> Liver function	2.050	.287	7.139	***
DeathR2 <-> Weight_Inc_R2	.750	.123	6.119	***

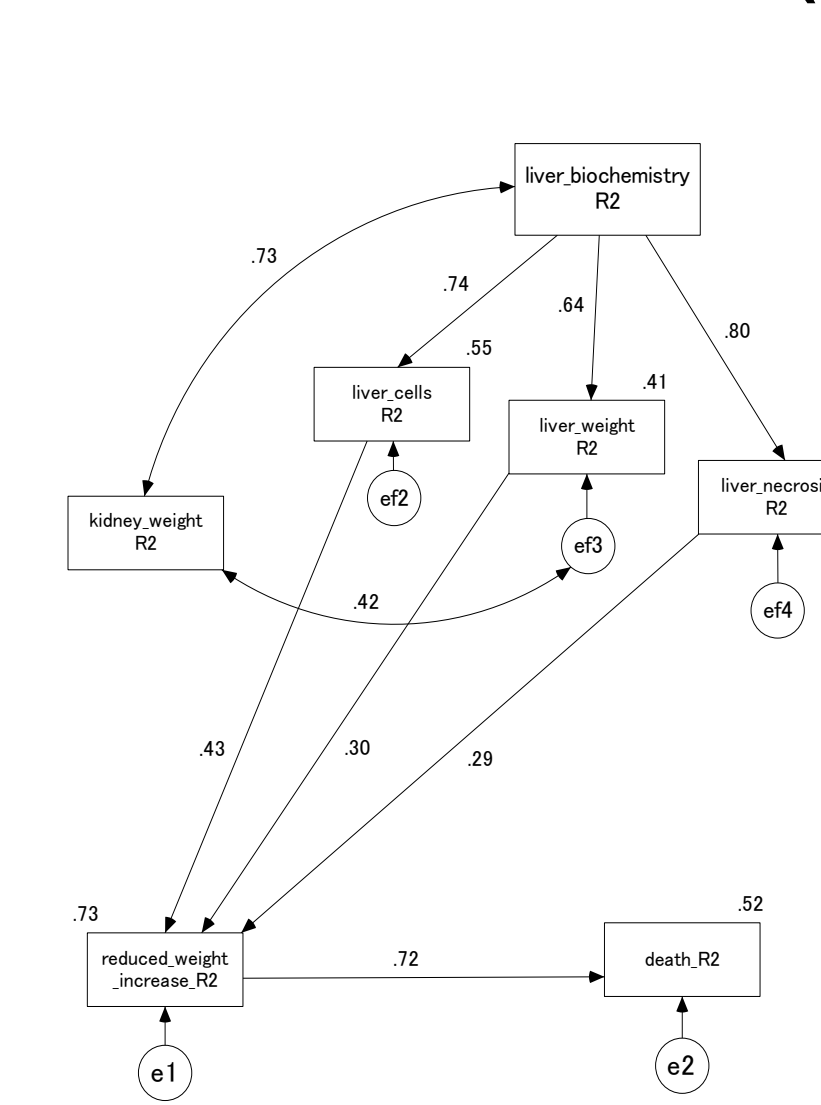
Covariance				
	MLE	S.D.	Test Statistics	Pr. ob.
Kidney_weightR2 <-> ef3	.859	.319	2.696	.003
Kidney_weightR2 <-> Liver_function	1.120	.201	5.578	***

Variance				
	MLE	S.D.	Test Statistics	Pr. ob.
Liver function	1.000			
ef3	1.785	.427	4.179	***
ef2	1.357	.439	3.092	.002
ef4	1.274	.457	2.788	.005
e1	.811	.209	3.881	***
e2	1.532	.377	4.066	***
ef1	.134	.476	.281	.779
Kidney_weightR2	2.367	.452	5.240	***

The error variance of the liver biochemistry is not significant. Hence we propose the following model revision.

### 3. Revision of Model (AIC=56.523)



Pass Coefficient				
	MLE	S.D.	Test Statistics	Prob.
Liver_cellR2 <-> Liver_biocR2	.619	.113	5.456	***
Liver_weightR2 <-> Liver_biocR2	.530	.106	4.991	***
Liver_necrosisR2 <-> Liver_biocR2	.734	.114	6.426	***
Weight_Inc_R2 <-> Liver_cellR2	.423	.121	3.487	***
Weight_Inc_R2 <-> Liver_necrosisR2	.261	.118	2.217	.027
Weight_Inc_R2 <-> Liver_weightR2	.302	.105	2.866	.004
DeathR2 <-> Weight_Inc_R2	.750	.123	6.113	***

Covariance				
	MLE	S.D.	Test Statistics	Prob.
Kidney_weightR2 <-> ef3	.860	.307	2.801	.005
Kidney_weightR2 <-> Liver_bioc_R2	2.335	.568	4.111	***

Variance				
	MLE	S.D.	Test Statistics	Prob.
Liver_biochemistryR2	4.379	1.021	4.269	***
ef2	1.384	.417	4.291	***
ef4	1.383	.425	3.252	.001
e1	1.350	.424	3.186	.001
e2	.808	.209	3.874	***
e2	1.532	.377	4.066	***
Kidney_weightR2	2.363	.451	5.238	***

### Acknowledgment

This work was supported by NEDO(The New Energy and Industrial Technology Development Organization) of Japan.