Israel JMP® Users Group Meeting
Online

15 September 2022 | Online

11:00 - 13:00 IDT

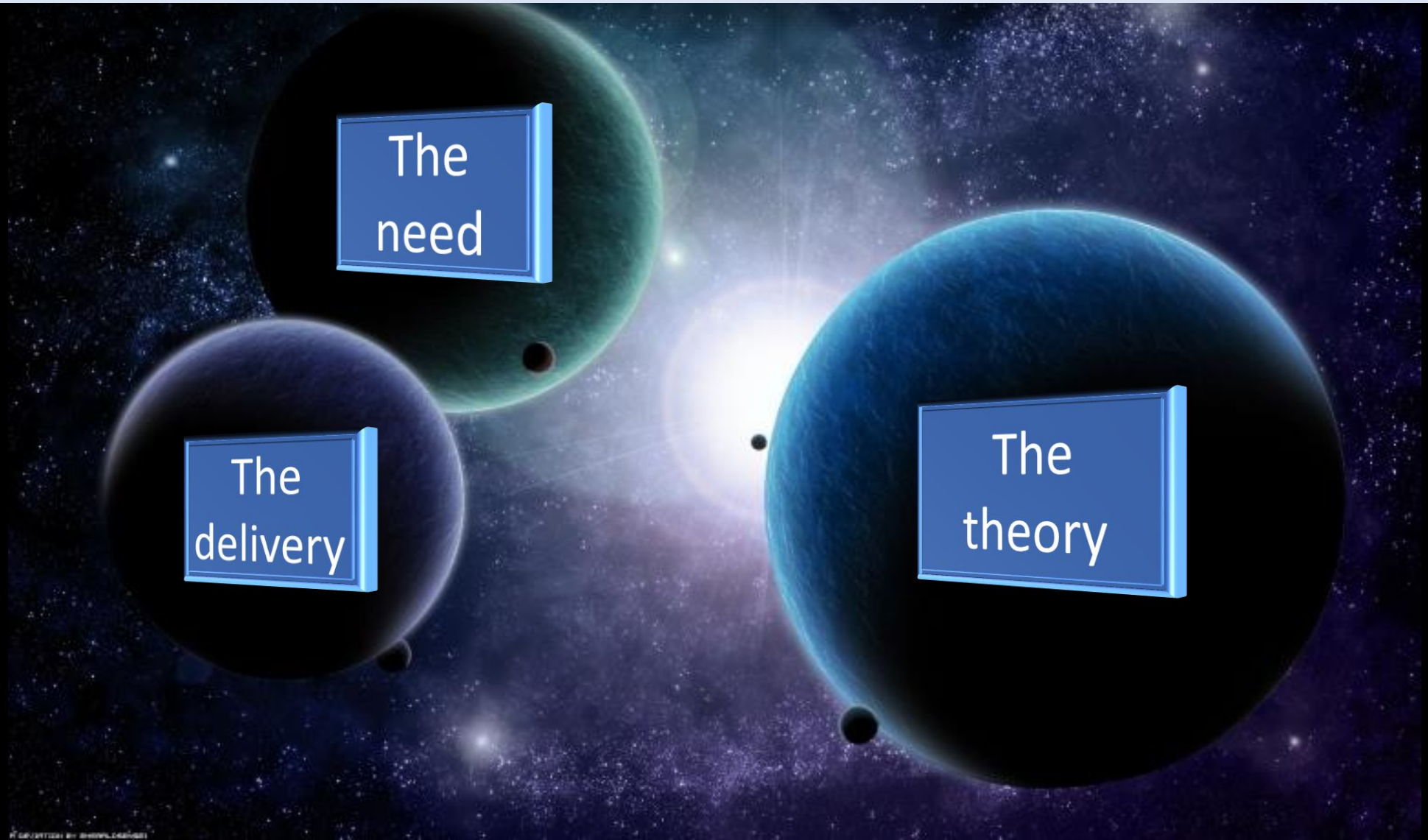
https://www.jmp.com/en_gb/events/seminars/user-group/israel-user-group-15sep22.html

Turning data into information, better decisions, and stronger organizations

A discussion on Information Quality and Quality by Design

Prof Ron S. Kenett

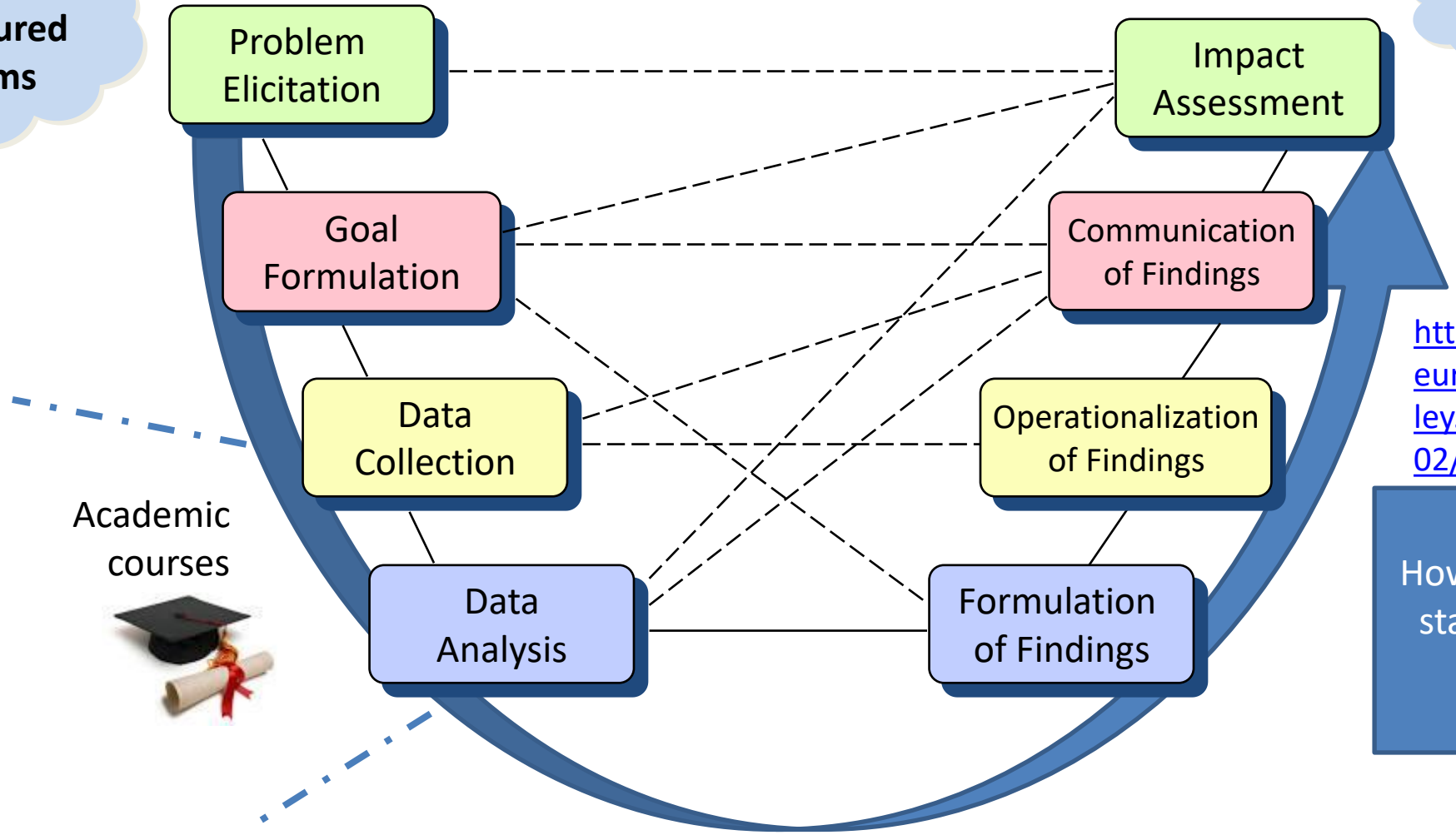
Turning data into information, better decisions, and stronger organizations



Statistics: A life cycle view

Unstructured problems

Lift curves, ROC
Confusion Matrix
AIC, MSE, InfoQ



https://chemistry-europe.onlinelibrary.wiley.com/doi/full/10.1002/ansa.202000159

How do we evaluate statistical/analytic work?

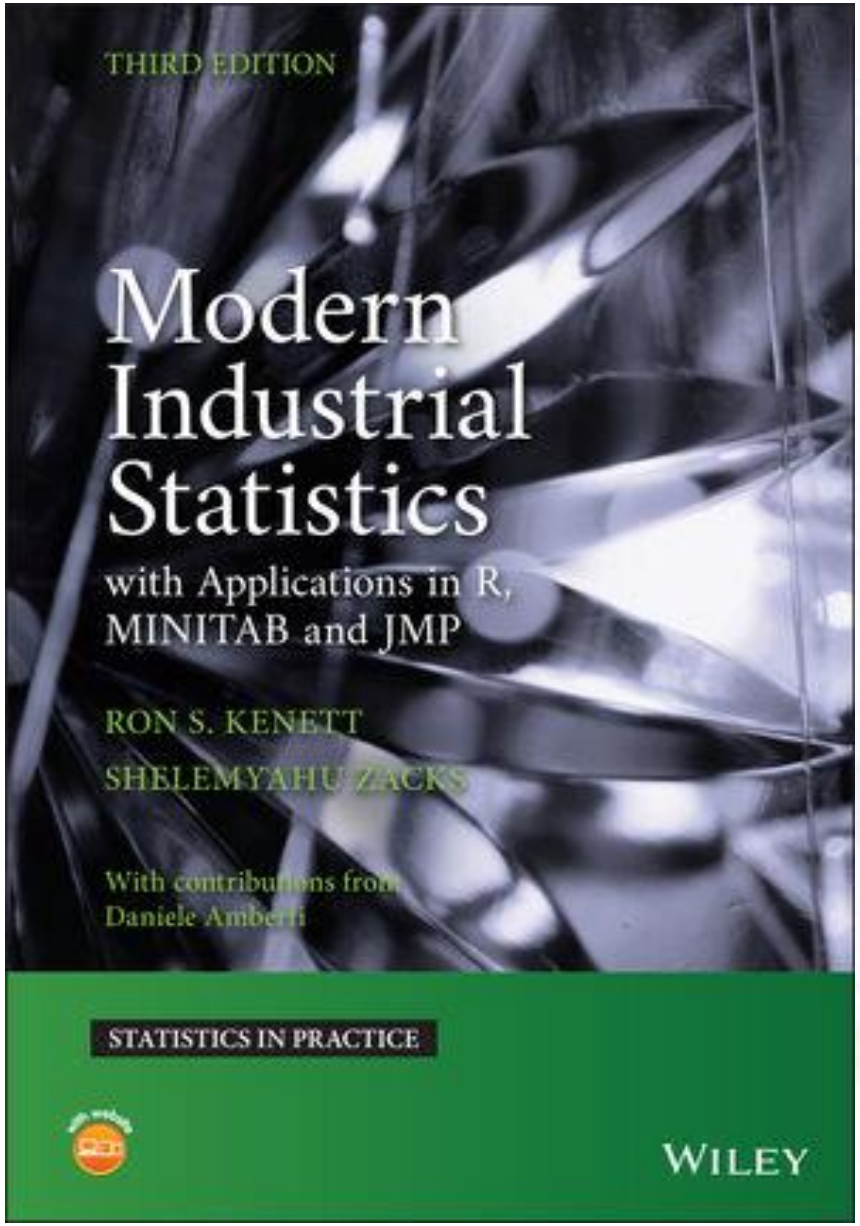
Kenett, R.S. (2015) Statistics: A Life Cycle View, *Quality Engineering* (with discussion), 27(1), pp. 111-129.

Kenett, R.S. and Thyregod, P. (2006) Aspects of statistical consulting not taught by academia, *Statistica Neerlandica*, 60 (3),396-412.

KPA Insights through analytics

Industrial Statistics

The methods



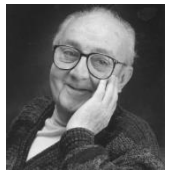
Statistical Methods

Design of Experiments, Reliablity

Epstein

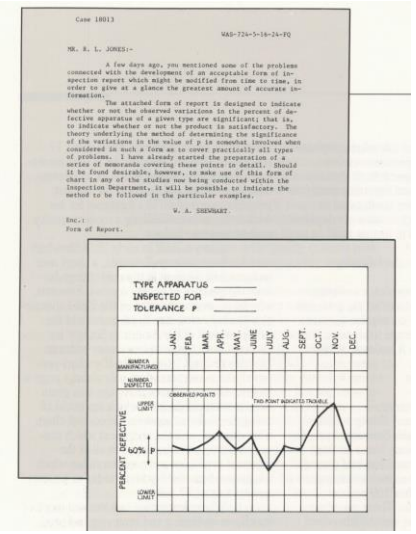
Taguchi

Box



Statistical Process Control

Shewhart



16/5/1924

Sampling

Descriptive Statistics

KPA
Insights through analytics

- Big data
- Artificial intelligence
- Data science
- Predictive analytics

The information

What is information quality?

Insight, knowldge

information

findings

statistical analysis

data

numbers

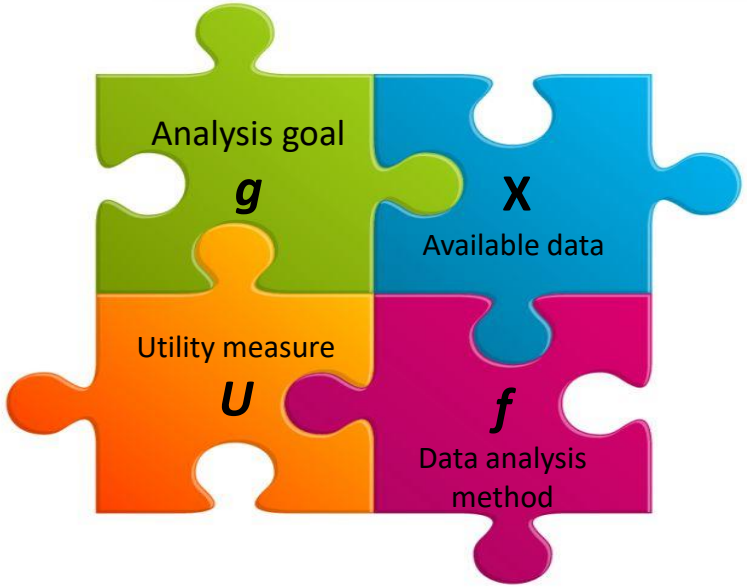
KPA
Insights through analytics

- Big data
- Artificial intelligence
- Data science
- Predictive analytics

Information Quality (InfoQ)

The information

The potential of a particular dataset to achieve a particular goal using a given empirical analysis method

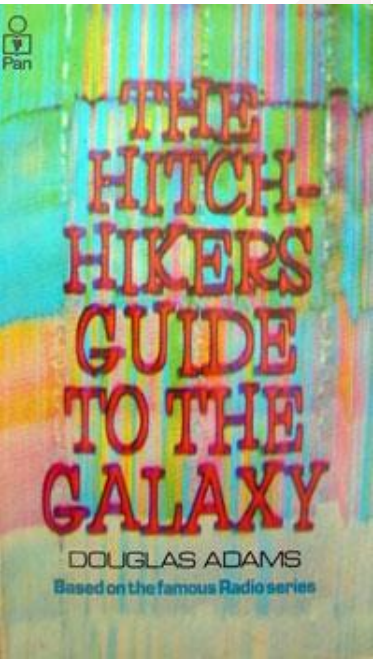


g	**A specific analysis goal**
X	**The available dataset**
f	**An empirical analysis method**
U	**A utility measure**

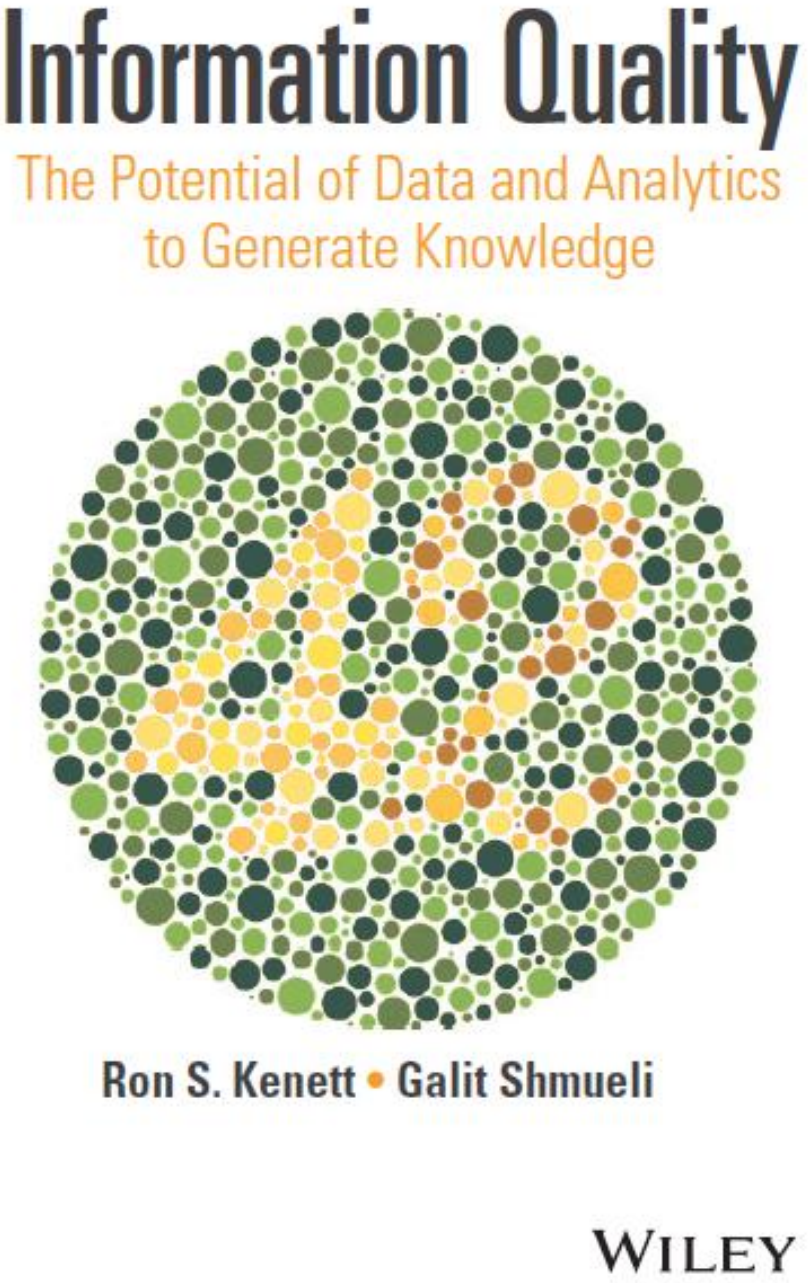
$$InfoQ(f,X,g) = U(f(X|g))$$

Kenett, R.S. and Shmueli , G. (2014) On Information Quality , *Journal of the Royal Statistical Society, Series A* (with discussion), Vol. 177, No. 1, pp. 3-38, 2014. http://ssrn.com/abstract=1464444.

KPA Insights through analytics



the "Answer to the Ultimate Question of Life, the Universe, and Everything,"



InfoQ Dimensions

The information

1. Data resolution
2. Data structure
3. Data integration

How

4. Temporal relevance
5. Chronology of data and goal
6. Generalizability
7. Operationalization
8. Communication

What

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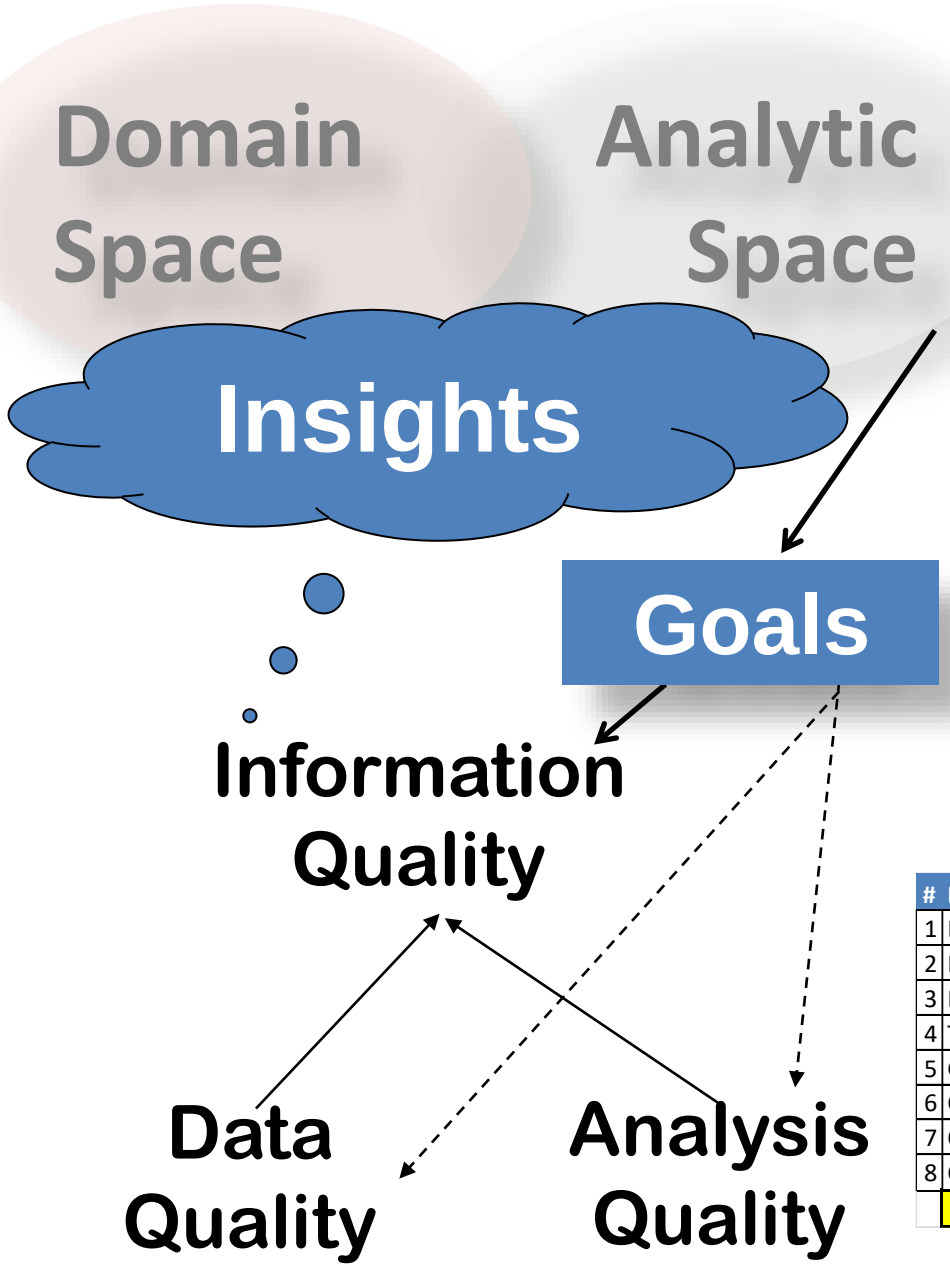
Insights through analytics

$$InfoQ(f,X,g) = U(f(X|g))$$



InfoQ Dimensions

The information

1. Data resolution
2. Data structure
3. Data integration
4. Temporal relevance
5. Chronology of data and goal
6. Generalizability
7. Operationalization
8. Communication

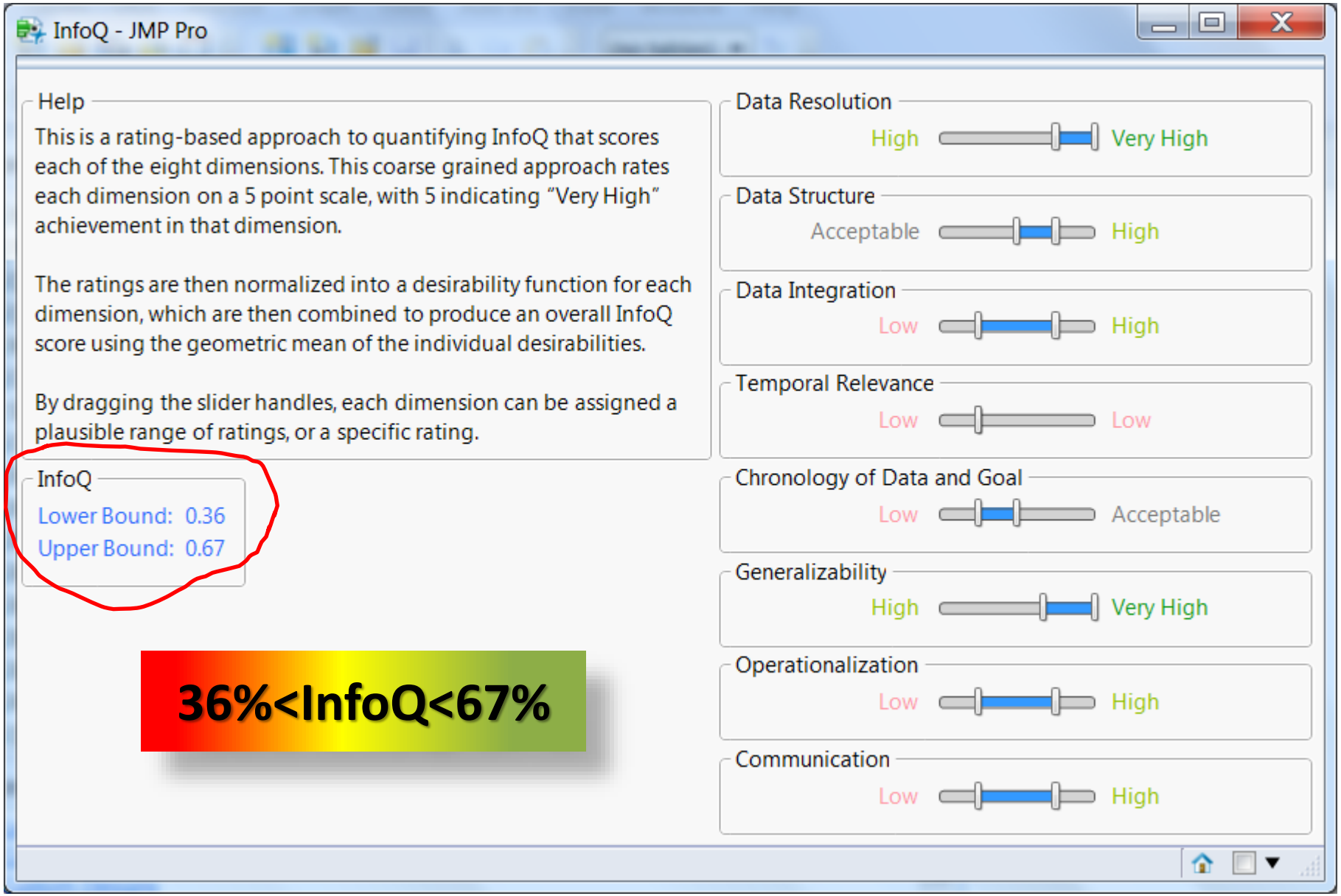
#	Dimension	Note	Value	Index
1	Data resolution		5	1.0000
2	Data structure		4	0.7500
3	Data integration		5	1.0000
4	Temporal relevance		5	1.0000
5	Generalizability		3	0.5000
6	Chronology of data and goal		5	1.0000
7	Concept operationalization		2	0.2500
8	Communication		3	0.5000
	InfoQ Score = 0.68			

InfoQ=68%

KPA Insights through analytics

$$InfoQ\ Score = [d_1(Y_1)\ \ d_2(Y_2)\ \ \ldots\ \ d_8(Y_8)]^{1/8}$$

The information



36%<InfoQ<67%

https://community.jmp.com/t5/JMP-Add-Ins/Calculate-InfoQ-score-with-JMP/ta-p/34898

KPA Insights through analytics

Data Analytic Methods

The method

The information

- Big data
- Artificial intelligence
- Data science
- Predictive analytics

Industrial Statistics Methods

Quality by Design

Design of Experiments, Reliability,

Process Improvement

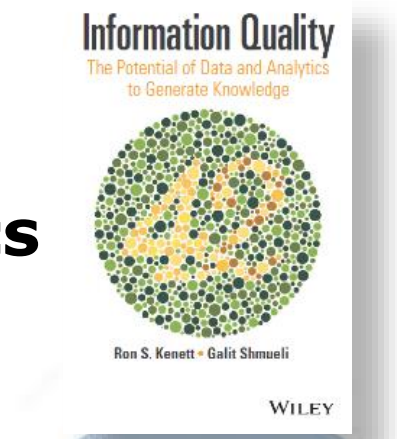
Statistical Process Control

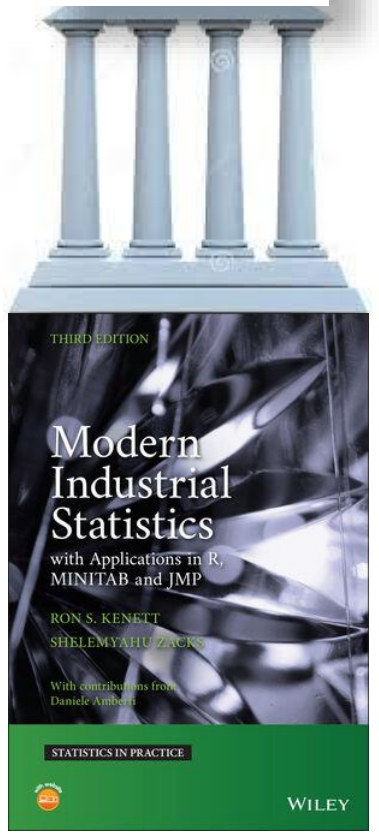
Inspection

Acceptance Sampling

Fire Fighting

Descriptive Statistics





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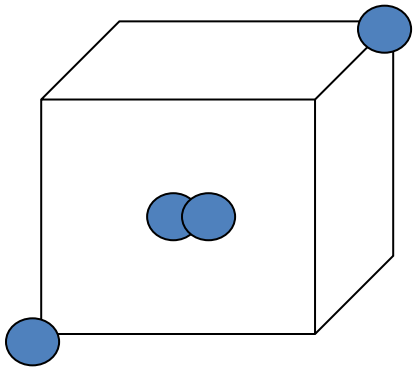
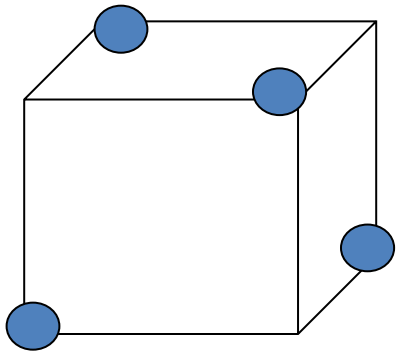
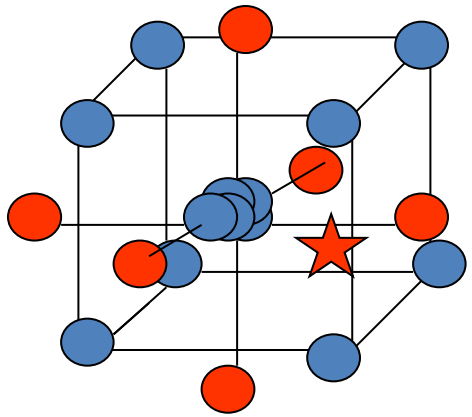
https://community.jmp.com/t5/JMP-Blog/A-QbD-update-Current-and-future-trends-in-Quality-by-Design/ba-p/258425

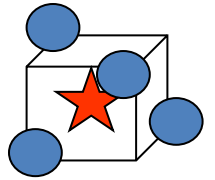
Information Quality and Quality by Design (QbD)

QbD column









Scoping

Initial assessment

Screening

Fractional designs

Optimizing

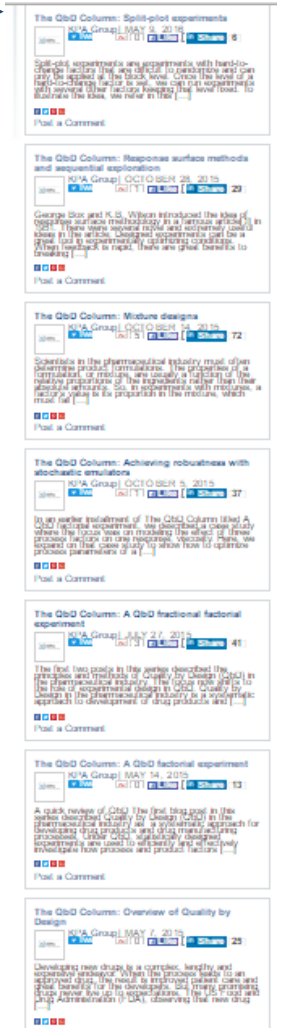
Response surfaces

Robustness

Robust designs

Gain Knowledge

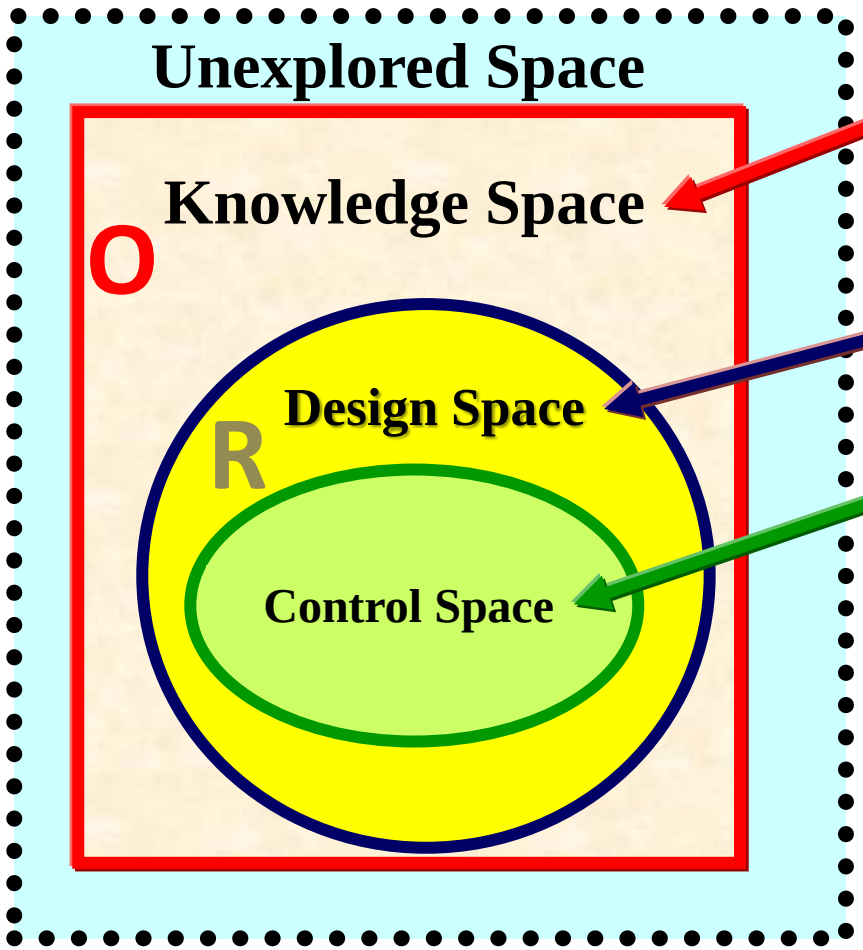
Build Confidence



KPA Insights through analytics

Background

Design Space, or, “Region of Immediate Interest”



Aggregated knowledge, past experiments, manufacturing experience, data from lab tests

Proven Acceptable Range

Normal Acceptable Range

Usually there will be a large "**operability region”**, **O**, of unknown, or vaguely known, extent within which it is possible to carry out experiments and within this, at a given stage of experimentation, a smaller "**region of immediate interest**“, **R**.

G. E. P. Box and N. R. Draper (1959) *A Basis for the Selection of a Response Surface Design,* Journal of the American Statistical Association, Vol. 54, No. 287, pp. 622-654

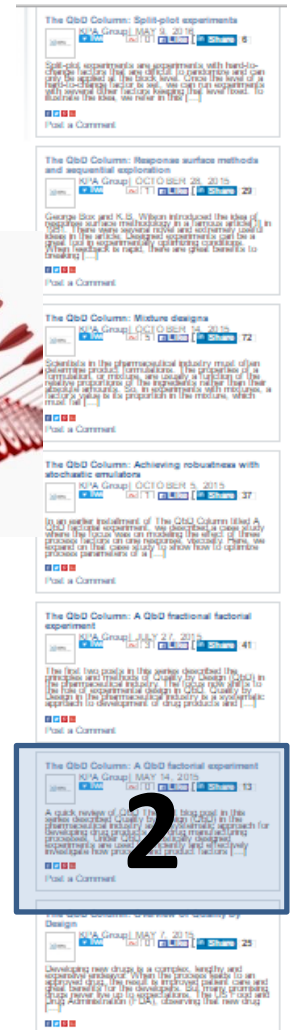
KPA Insights through analytics

Blog 2: Factorial experiments

Responses: 1) Assay of active ingredient, 2) In vitro permeability lower confidence interval, 3) In vitro permeability upper confidence interval, 4) Assay of methylparaben, 5) Assay of propylparaben, 6) **Viscosity** and 7) pH values.

Factors: A) Temperature of reaction, B) Blending time and C) Cooling time.

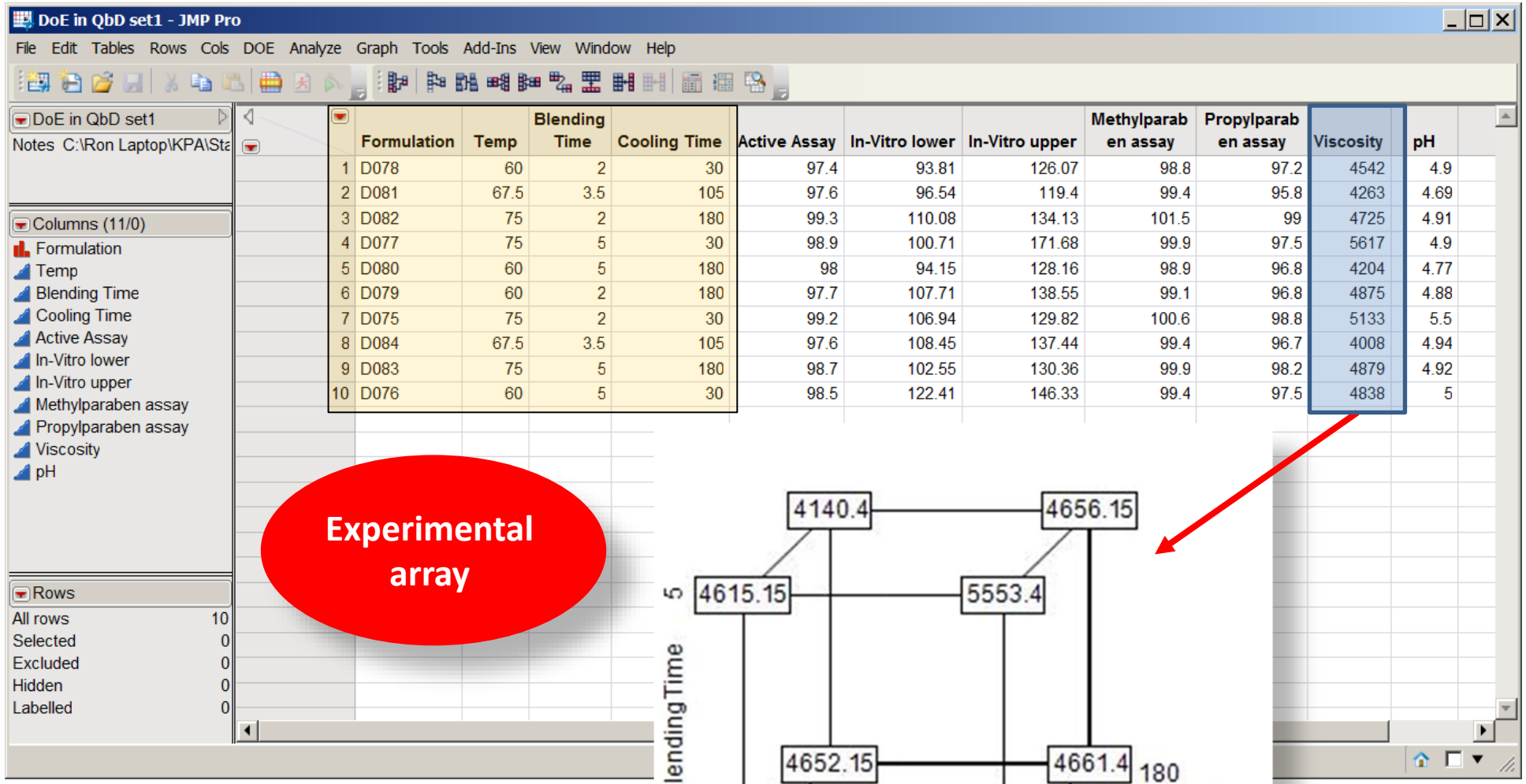
Set up a Design space



https://community.jmp.com/t5/JMP-Blog/The-QbD-Column-A-QbD-factorial-experiment/ba-p/30592

KPA Insights through analytics

Factors, Levels and Responses



	Formulation	Temp	Blending Time	Cooling Time	Active Assay	In-Vitro lower	In-Vitro upper	Methylparaben assay	Propylparaben assay	Viscosity	pH
1	D078	60	2	30	97.4	93.81	126.07	98.8	97.2	4542	4.9
2	D081	67.5	3.5	105	97.6	96.54	119.4	99.4	95.8	4263	4.69
3	D082	75	2	180	99.3	110.08	134.13	101.5	99	4725	4.91
4	D077	75	5	30	98.9	100.71	171.68	99.9	97.5	5617	4.9
5	D080	60	5	180	98	94.15	128.16	98.9	96.8	4204	4.77
6	D079	60	2	180	97.7	107.71	138.55	99.1	96.8	4875	4.88
7	D075	75	2	30	99.2	106.94	129.82	100.6	98.8	5133	5.5
8	D084	67.5	3.5	105	97.6	108.45	137.44	99.4	96.7	4008	4.94
9	D083	75	5	180	98.7	102.55	130.36	99.9	98.2	4879	4.92
10	D076	60	5	30	98.5	122.41	146.33	99.4	97.5	4838	5

KPA Insights through analytics

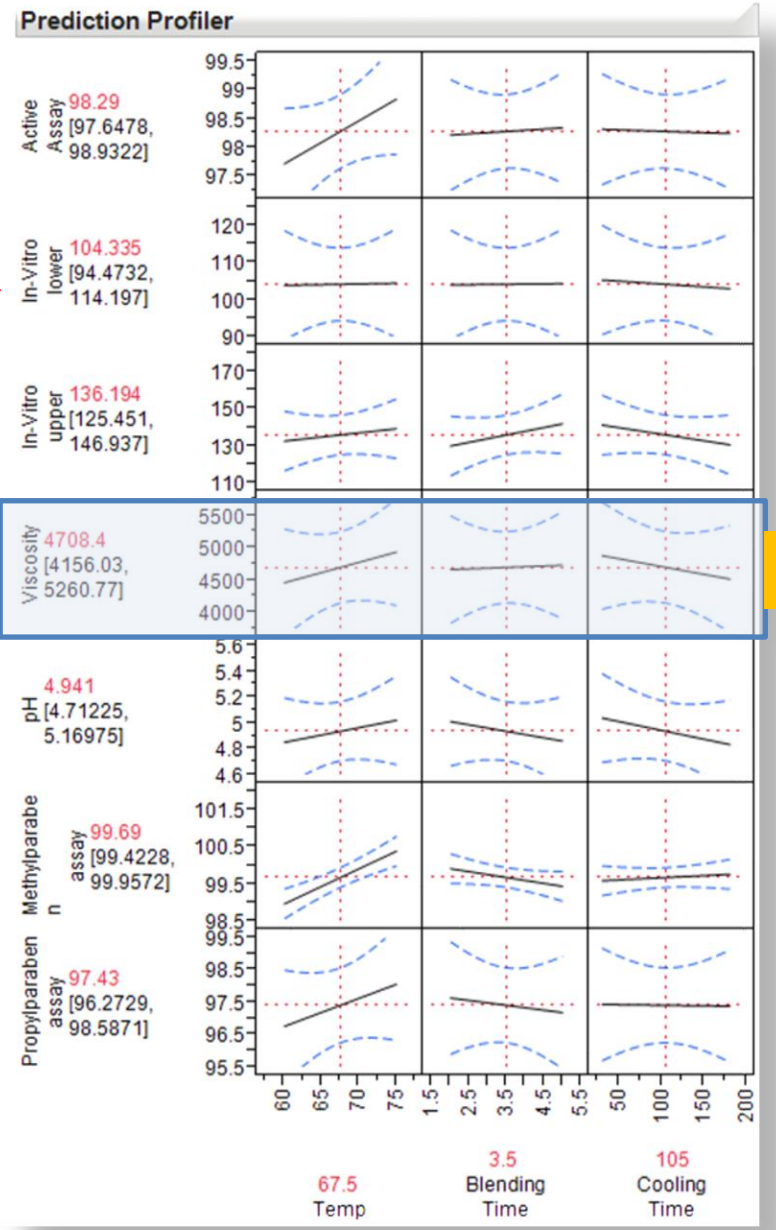
Prediction Profiler

Viscosity

Term	Estimate	Std Error	t Ratio
Temp(60,75)	236.875	194.0543	1.22
Cooling Time(30,180)	-180.875	194.0543	-0.93
Blending Time*Cooling Time	-162.125	194.0543	-0.84
Temp*Blending Time	126.625	194.0543	0.65
Temp*Cooling Time	-105.625	194.0543	-0.54
Blending Time(2,5)	32.875	194.0543	0.17

Spec Limits

Response	LSL	USL
Active Assay	95	105
In-Vitro Lower	75	.
In-Vitro Upper	.	133
D90	1	2
A Assay	95	105
B Assay	95	105
Viscosity	4000	6000
pH	4.7	5.7



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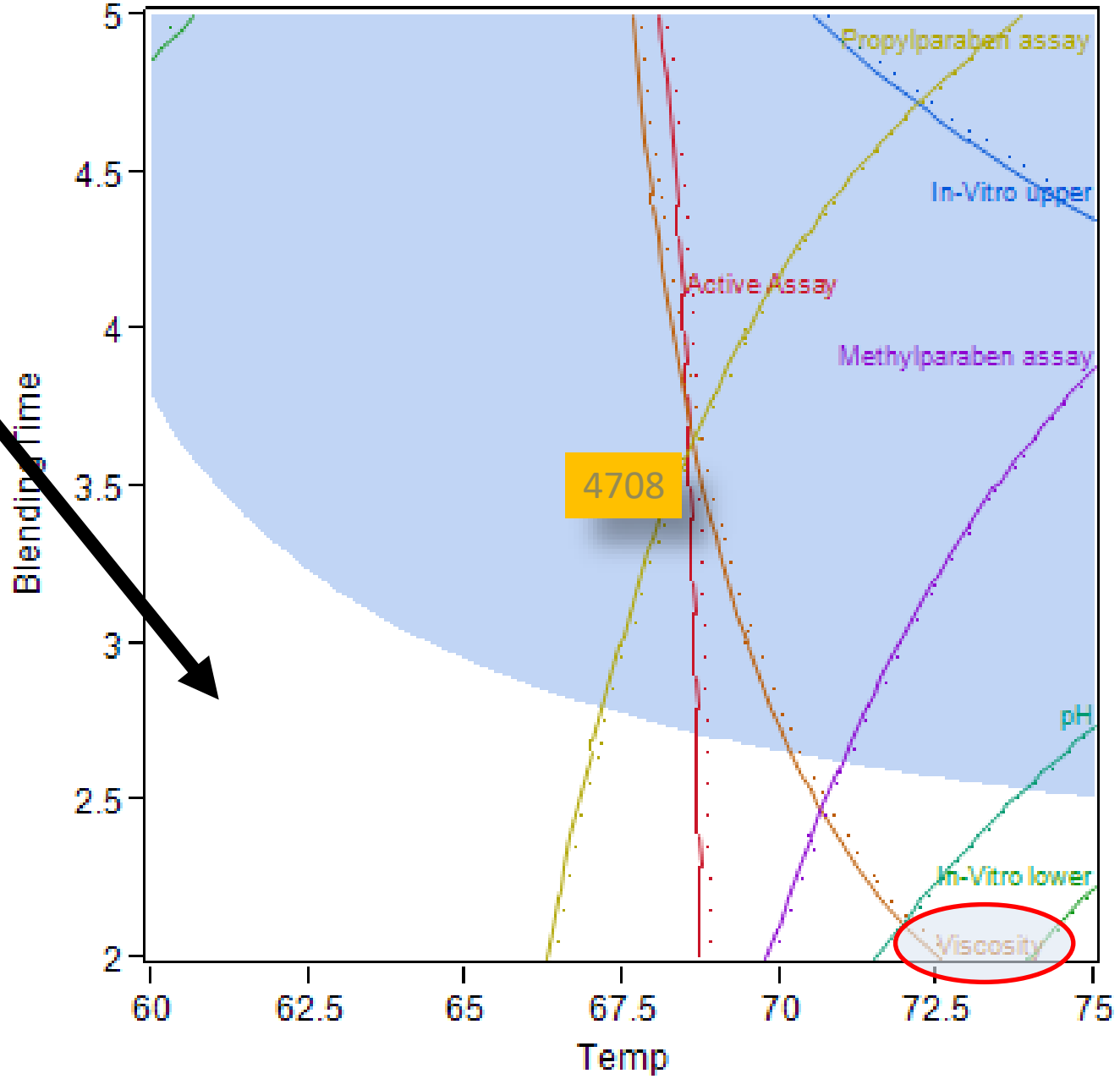
KPA Insights through analytics

Design Space



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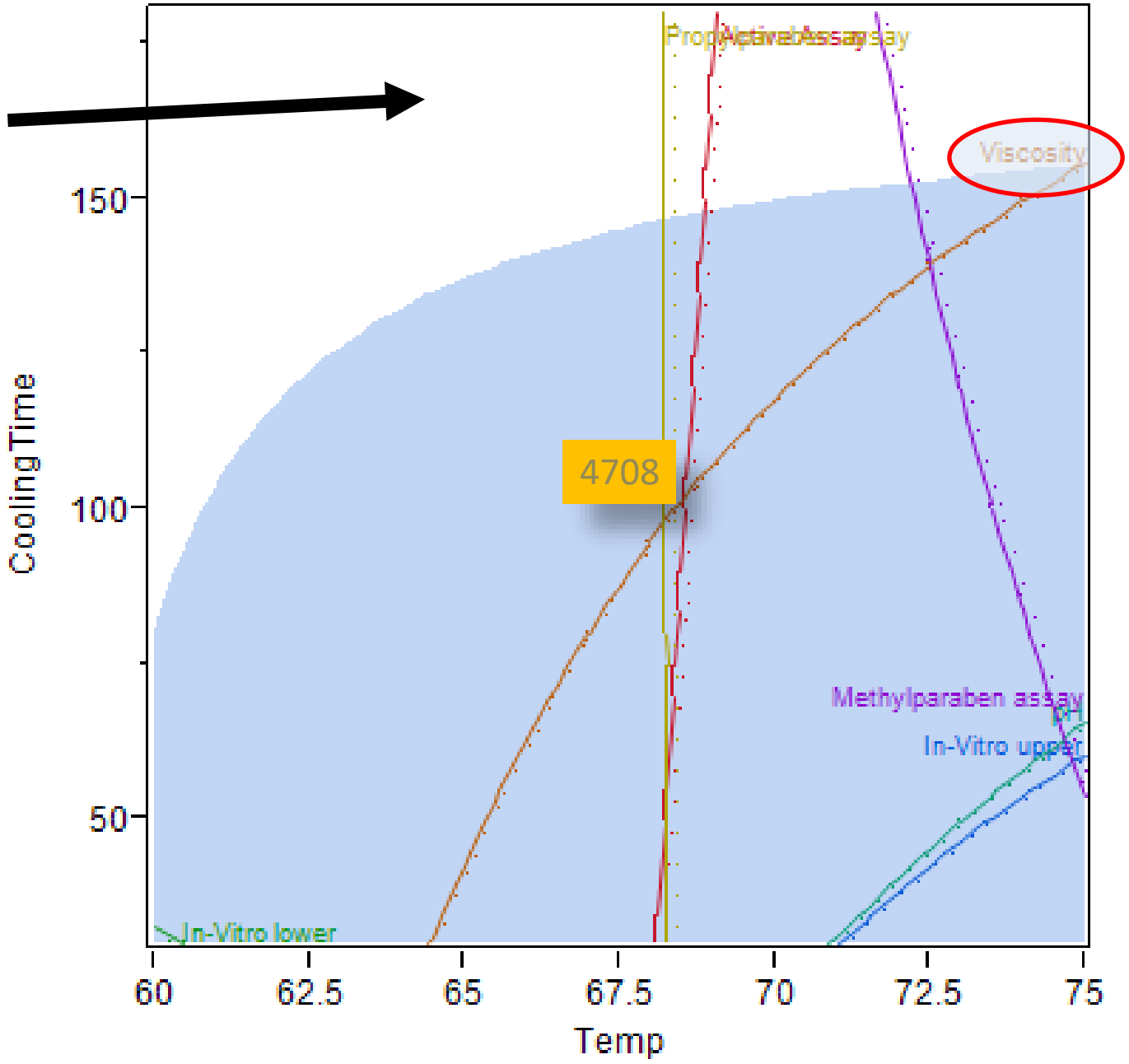
Insights through analytics

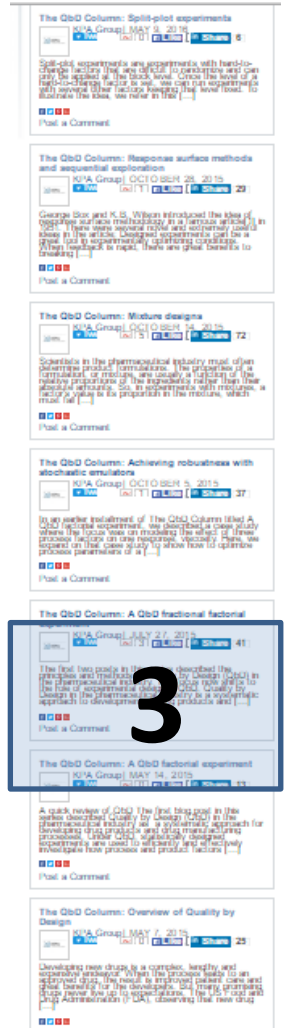
Design Space



KPA
Insights through analytics

Blog 3: Fractional Factorial Experiments

We explore the process of preparing **nanosuspension formulations for water insoluble drugs**. Nanosuspensions involve colloidal dispersions of discrete drug particles, which are stabilized with polymers and/or surfactants. This permits to achieve improved bioavailability by **using small particles, which increase the dissolution rate for drugs with poor solubility.** The process begins with larger particles. Then milling is used to reduce their size. **The study examines the use of microfluidization at the milling stage**.



https://community.jmp.com/t5/JMP-Blog/The-QbD-Column-A-QbD-fractional-factorial-experiment/ba-p/30619

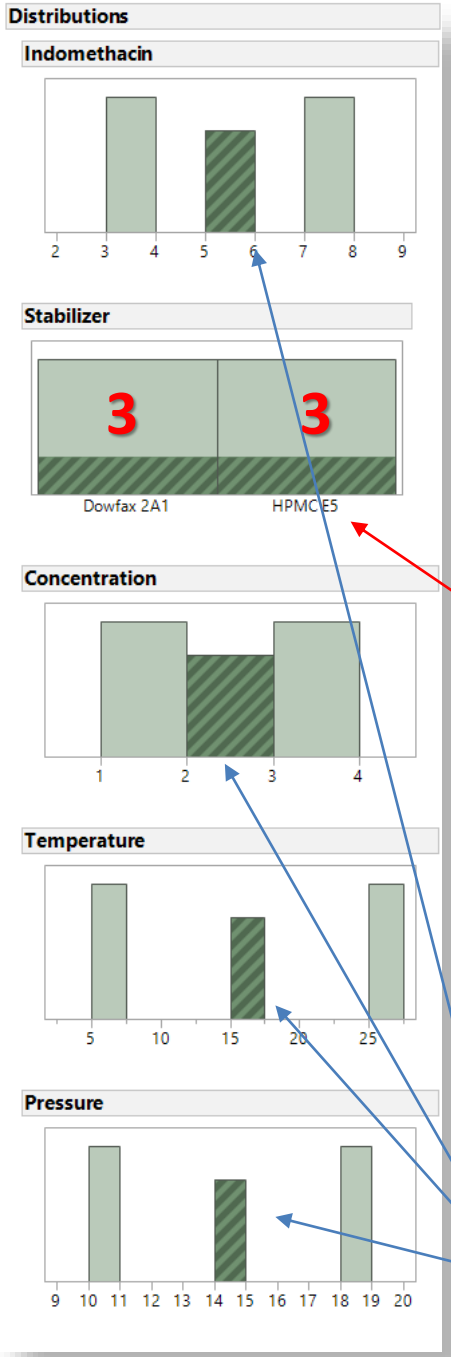
KPA Insights through analytics

Fractional Factorial Experiments

The experiment is a two-level fractional factorial with **six center points**. The fractional factorial used here is a 2^{5-1} design set at the extreme levels of each of the quantitative factors. The 2^{5-1} design permits estimation of all the main effects and all the two-factor interactions.

Is there nonlinearity in responses?

We derive a formal significance test of nonlinearity by adding an "indicator" column which has the value 1 for the center points and 0 for all other points.



DOE - Screening Design - JMP

File Edit Tables Rows Cols DOE Analyze Graph Tools View Window Help

Screening Design

Responses

Add Response | Remove | Number of Responses...

Response Name	Goal	Lower Limit	Upper Limit	Importance
Y	Maximize	.	.	.

optional item

Factors

Continuous | Discrete Numeric | Categorical | Remove | Add N Factors 1

Name	Role	Values	
Idomethacin	Continuous	3	7
Concentration	Continuous	1	3
Pressure	Continuous	10	18
Temperature	Continuous	5	25
X5	Categorical	Dowfax	HPMC

Stabilizer

Fractional Factorial

Display and Modify Design

Coded Design

Design Evaluation

Output Options

Run Order: Randomize

Make JMP Table from design plus

Number of Center Points: 6

Number of Replicates: 0

Make Table

Back

Center points

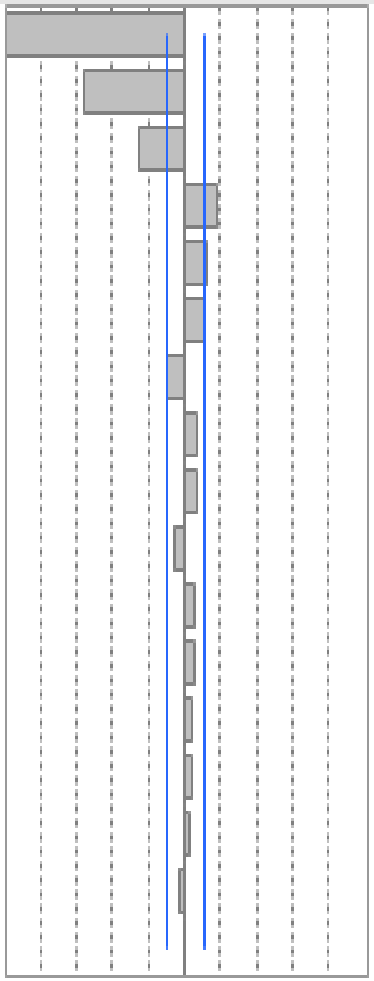
KPA Insights through analytics

Parameter Estimates

Sorted Parameter Estimates — **MeanSize90**

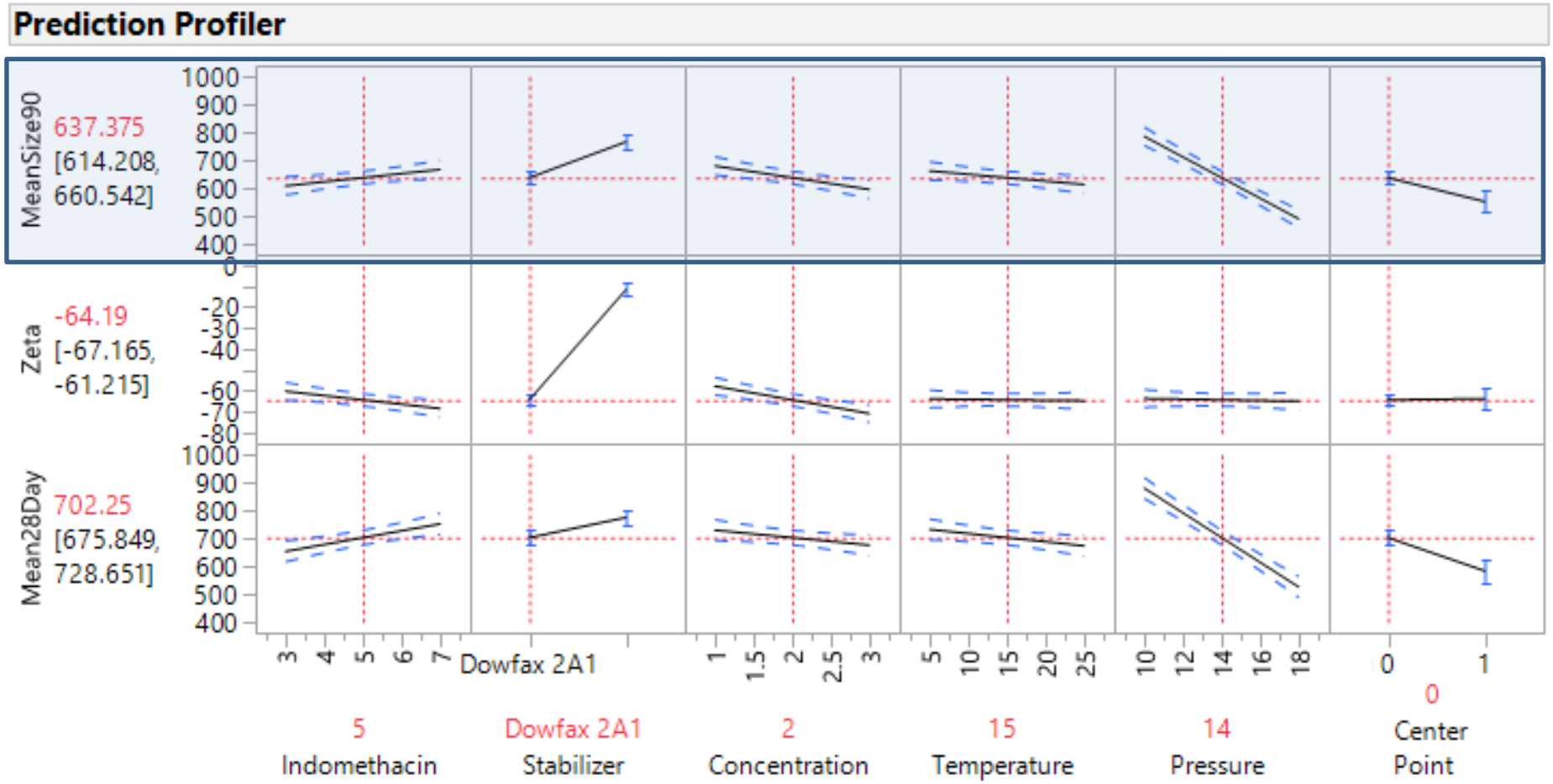
mean particle size after 90 minutes of milling, before storage.

Term	Estimate	Std Error	t Ratio	Prob>|t|
Pressure	-38.09375	1.475053	-25.83	<.0001*
Stabilizer[Dowfax 2A1]	-81	5.649023	-14.34	0.0001*
Concentration	-38	5.900212	-6.44	0.0030*
Center Point[0]	25.6875	5.649023	4.55	0.0104*
Indomethacin	9.8125	2.950106	3.33	0.0292*
Stabilizer[Dowfax 2A1]*Center Point[0]	17	5.649023	3.01	0.0396*
Temperature	-1.5875	0.590021	-2.69	0.0546
(Temperature-15)*(Pressure-14)	0.278125	0.147505	1.89	0.1324
(Indomethacin-5)*Stabilizer[Dowfax 2A1]	4.875	2.950106	1.65	0.1738
Stabilizer[Dowfax 2A1]*(Temperature-15)	-0.85	0.590021	-1.44	0.2231
(Indomethacin-5)*(Pressure-14)	1.046875	0.737526	1.42	0.2288
(Concentration-2)*(Pressure-14)	1.9375	1.475053	1.31	0.2593
(Indomethacin-5)*(Concentration-2)	3.625	2.950106	1.23	0.2865
(Indomethacin-5)*(Temperature-15)	0.34375	0.295011	1.17	0.3087
Stabilizer[Dowfax 2A1]*(Pressure-14)	1.125	1.475053	0.76	0.4881
Stabilizer[Dowfax 2A1]*(Concentration-2)	-4.125	5.900212	-0.70	0.5230
(Concentration-2)*(Temperature-15)	0.025	0.590021	0.04	0.9682



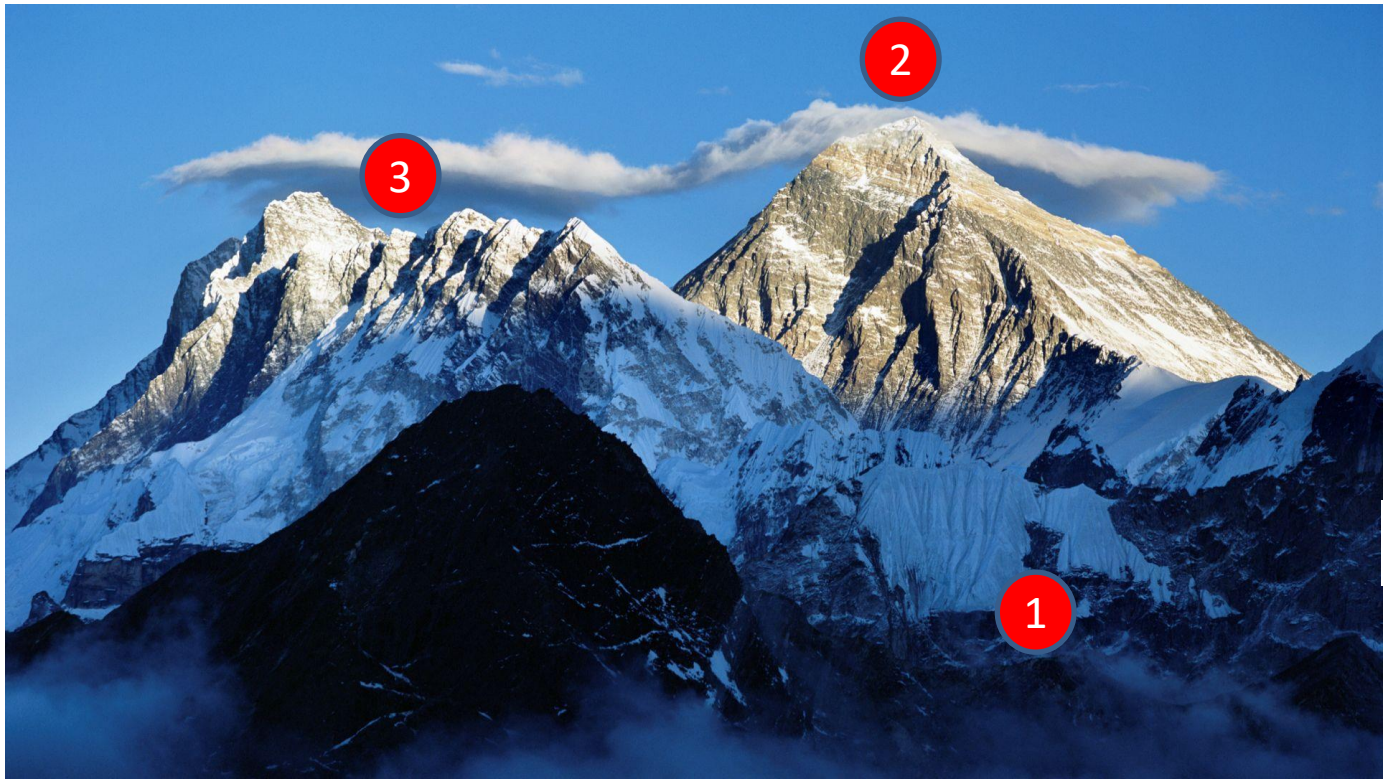
KPA Insights through analytics

Prediction Profiler



KPA Insights through analytics

Blog 4: Robustness with Stochastic Emulators



Quality Technology & Quantitative Management
Vol. 3, No. 2, pp. 161-177, 2006

QTQM
© ICAQM 2006

Achieving Robust Design from Computer Simulations

Ron A. Bates[1], Ron S. Kenett[2], David M. Steinberg[3] and Henry P. Wynn[4]
[1,4]London School of Economics, London, UK
[2]KPA Ltd., Raanana, ISRAEL
[3]Tel Aviv University, Tel Aviv, ISRAEL and KPA Ltd.
(*Received* December 2004, *accepted* July 2005)

Perform robust design analysis


1. Bad


2. Optimal


3. Robust

https://community.jmp.com/t5/JMP-Blog/The-QbD-Column-Achieving-robustness-with-stochastic-emulators/ba-p/30644

KPA Insights through analytics

Robustness with Stochastic Emulators

The study refers to a formulation of a generic product designed to match the properties of an existing brand using in vitro tests. A 90% confidence interval for the ratio of the median in vitro release rate in the generic and brand products is computed, and expressed as a percentage. If the interval falls within the limits of **75% to 133.33%,** the generic and brand products are considered equivalent.

The **eight responses** listed in the SUPAC* standard that are considered in setting up the bioequivalence process design space are: 1) Assay of active ingredient, 2) In vitro release rate lower confidence limit, 3) In vitro release rate upper confidence limit, 4) 90th percentile of particle size, 5) Assay of material A, 6) Assay of material B, 7) Viscosity and 8) pH values.

Three process factors are considered: A) Temperature of reaction, B) Blending time and C) Cooling time. The experimental design consisted of a 2^3 factorial experiment with 2 center points.

*Scale-up and Post-Approval Changes

Key Steps

The key steps of the stochastic emulator approach are as follows:

1. **Begin with a model** that relates the input factors to the system outputs.

2. **Characterize the uncertainty in the system**. Describe how the input factors are expected to vary about their nominal process settings.

3. Lay out an experimental design in the **input factors** at nominal settings.

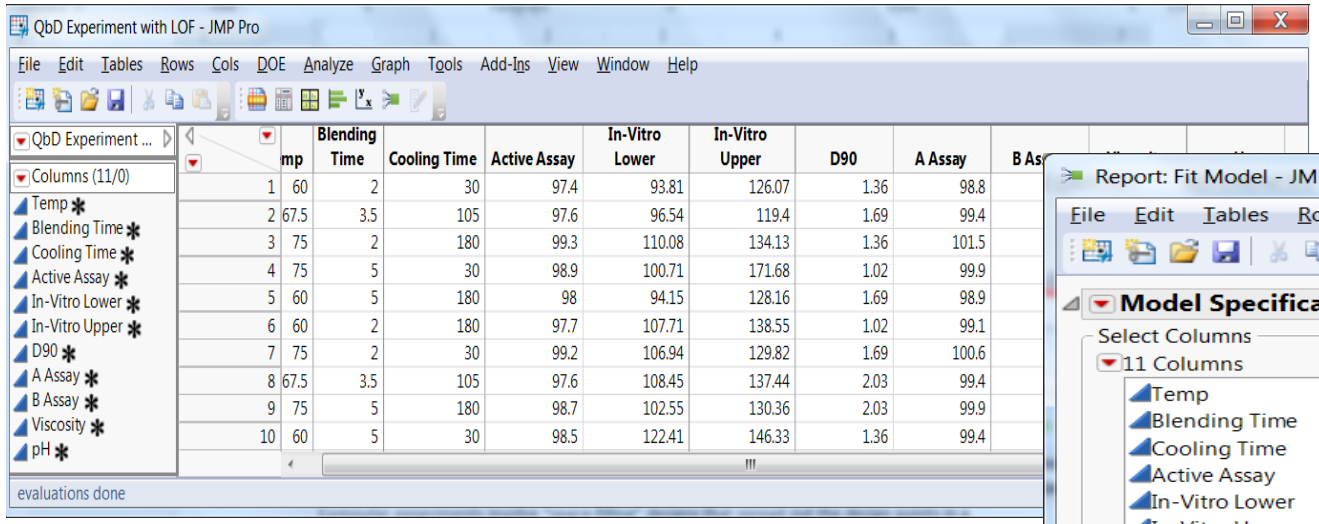
4. Generate **simulated** data from the noise distributions at all the nominal settings with a **space-filling design**.

5. **Summarize** the simulated data at each nominal setting by critical response variables (like desirability and defect rate in our study).

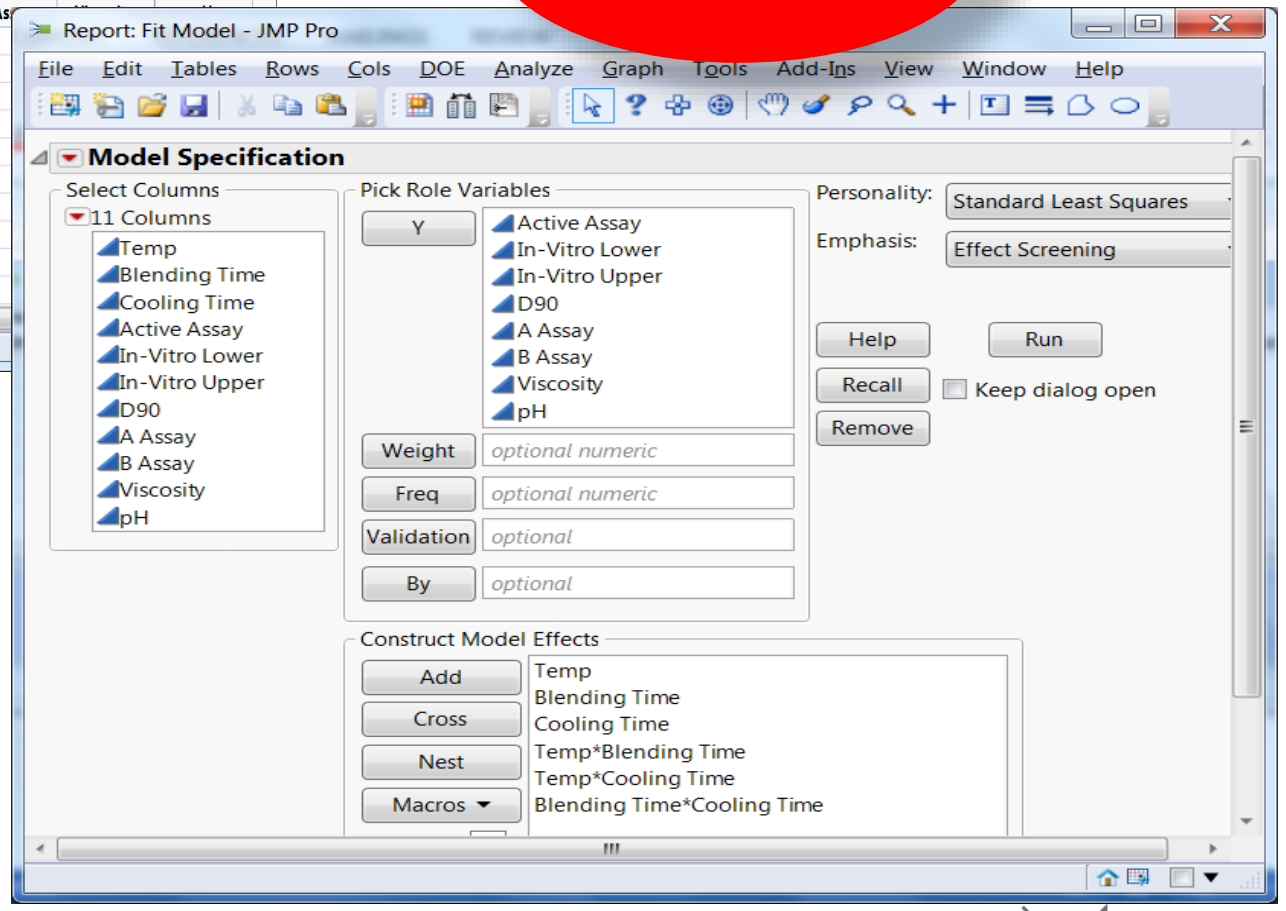
6. Construct statistical models that relate critical response variables to the design factor settings using **the Gaussian process model** option in JMP.

7. **Optimize** the choice of the factor settings for all critical outcomes. Here we want the process to have both on target performance and robustness (JMP allows us to do this by linking and optimizing profilers).

Robustness Design Analysis



Perform robust design analysis



Spec Limits

Response	LSL	USL
Active Assay	95	105
In-Vitro Lower	75	.
In-Vitro Upper	.	133
D90	1	2
A Assay	95	105
B Assay	95	105
Viscosity	4000	6000
pH	4.7	5.7

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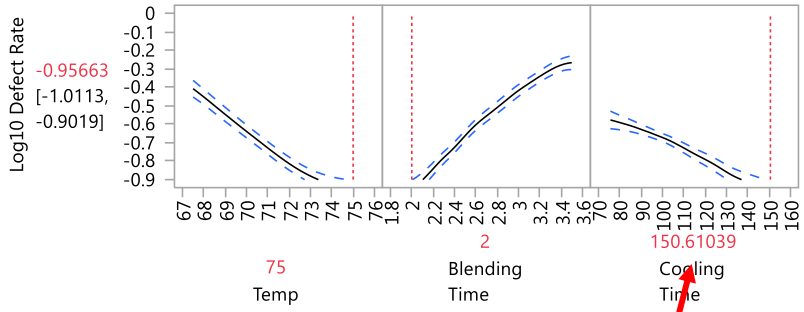
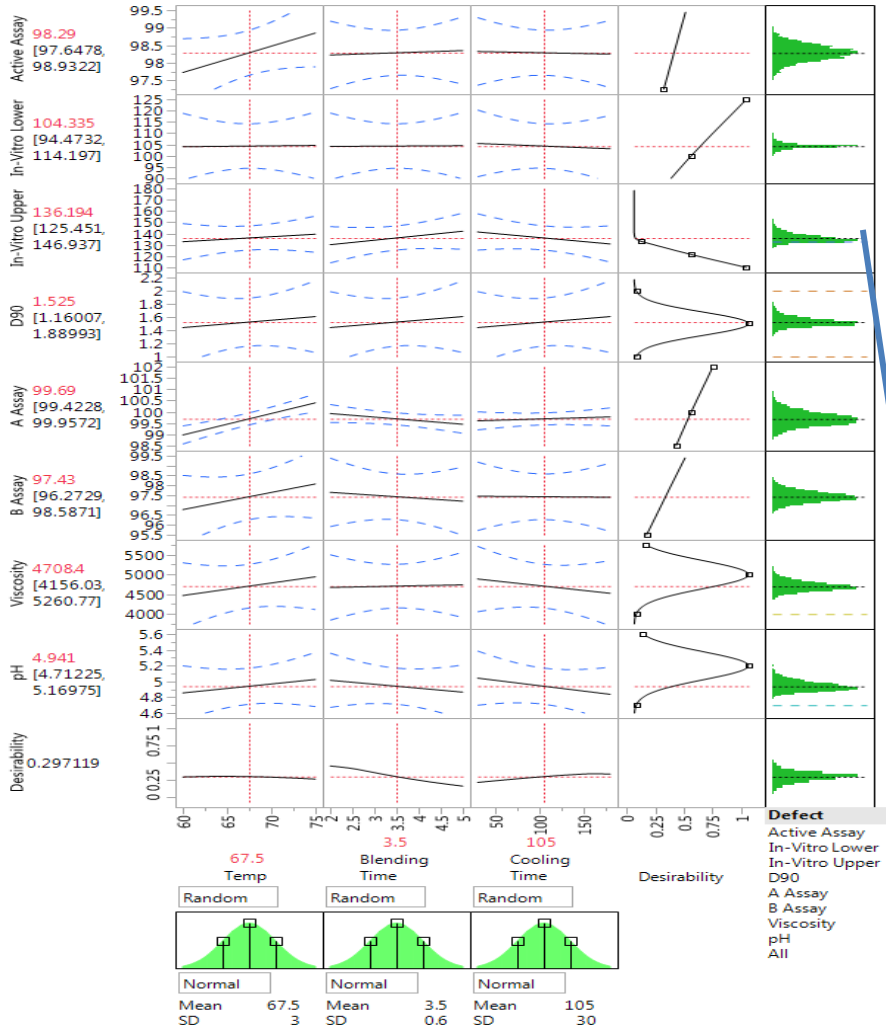
Linked Profilers

When we run the simulation on the noise in the design factors (Temp=75, Blending Time=2, Cooling Time=150.6), we achieve an overall desirability of 0.53 and a defect rate of **0.09.**

From stochastic emulator





Spec Limits		
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D90	1	2
A Assay	95	105
B Assay	95	105
Viscosity	4000	6000
pH	4.7	5.7

Defect	Rate	Mean	SD
Active Assay	0	98.2858	0.23513
In-Vitro Lower	0	104.328	1.23656
In-Vitro Upper	0.8132	136.118	3.84853
D90	0	1.52591	0.07515
A Assay	0	99.6849	0.31574
B Assay	0	97.4247	0.28845
Viscosity	0	4704.41	125.355
pH	0	4.93924	0.06344
All	0.8132		

Defect	Rate	Mean	SD
Active Assay	0	99.0765	0.35571
In-Vitro Lower	0	108.038	3.52803
In-Vitro Upper	0.1965	129.974	4.22125
D90	0.0002	1.60919	0.08642
A Assay	0	100.977	0.50918
B Assay	0	98.6052	0.44215
Viscosity	0	4784.62	98.9
pH	0.0003	5.1738	0.11701
All	0.1968		

Setting	Temp	Blending Time	Cooling Time
Optimised	75	2	105.04169

81% => 19% => 9%

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Blog 5: Mixture Designs

The properties of a formulation, or mixture, are a function of the relative proportions of the ingredients rather than their absolute amounts. **This type of data is called mixture or compositional data (CoDa)** In experiments with mixtures, a factor's value is its proportion in the mixture, which must fall between zero and one.

We use here an extreme vertices design with four components to compute formulation compositions with the following constraints applied to the weight fractions of corresponding formulation components: for **Ibuprofen**, 0.25≤wt. fraction≤0.75; for **HPMC**, 0.01≤wt. fraction≤0.03; for **MCC**: 0.19≤wt. fraction≤0.57; for **Eudragit** L 100-55: 0.05≤wt. fraction≤0.15.

https://community.jmp.com/t5/JMP-Blog/The-QbD-Column-Mixture-designs/ba-p/30651

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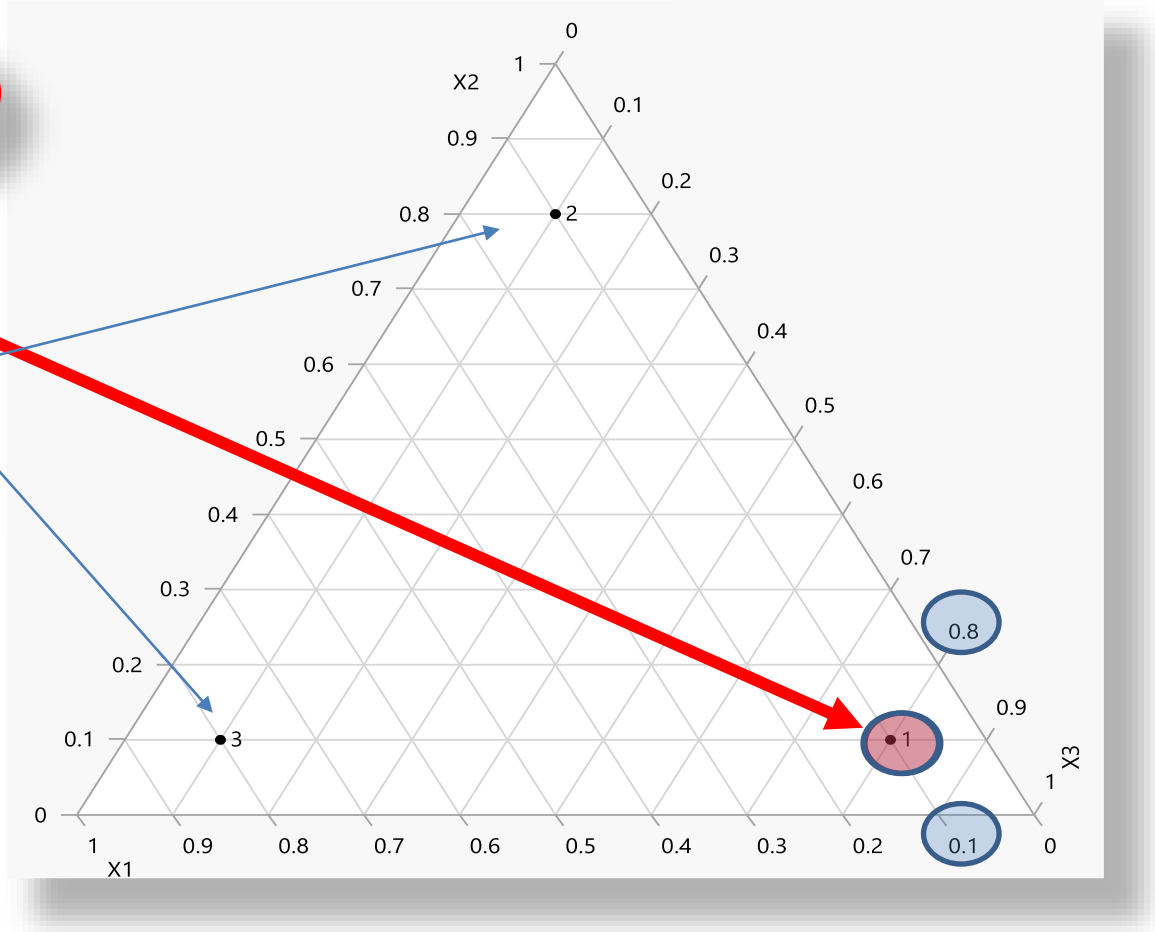
Mixture Designs

How to represent formulations?

1. [0.1, 0.1, 0.8]
2. [0.1, 0.8, 0.1]
3. [0.8, 0.1, 0.1]



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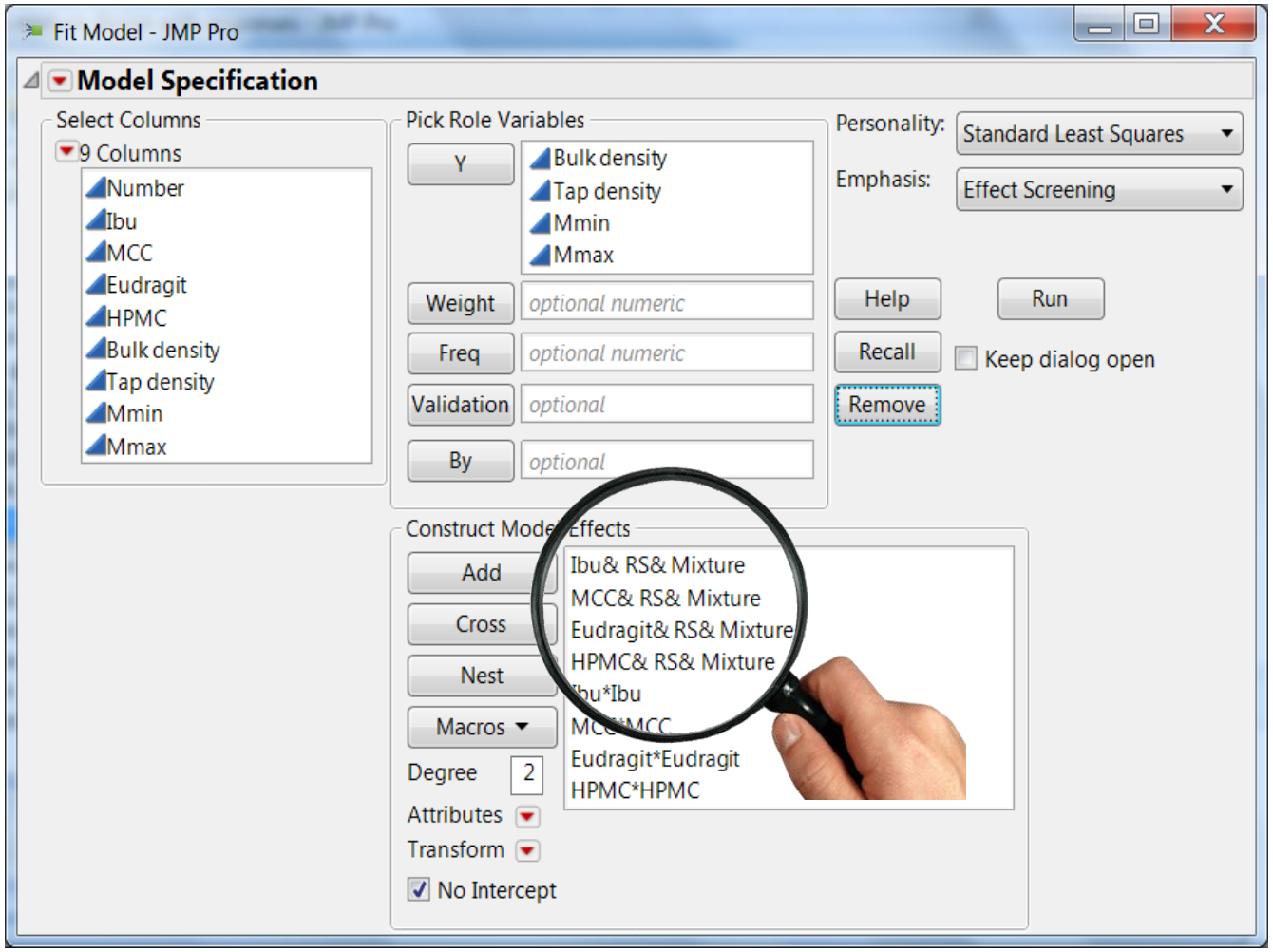
Mixture Designs



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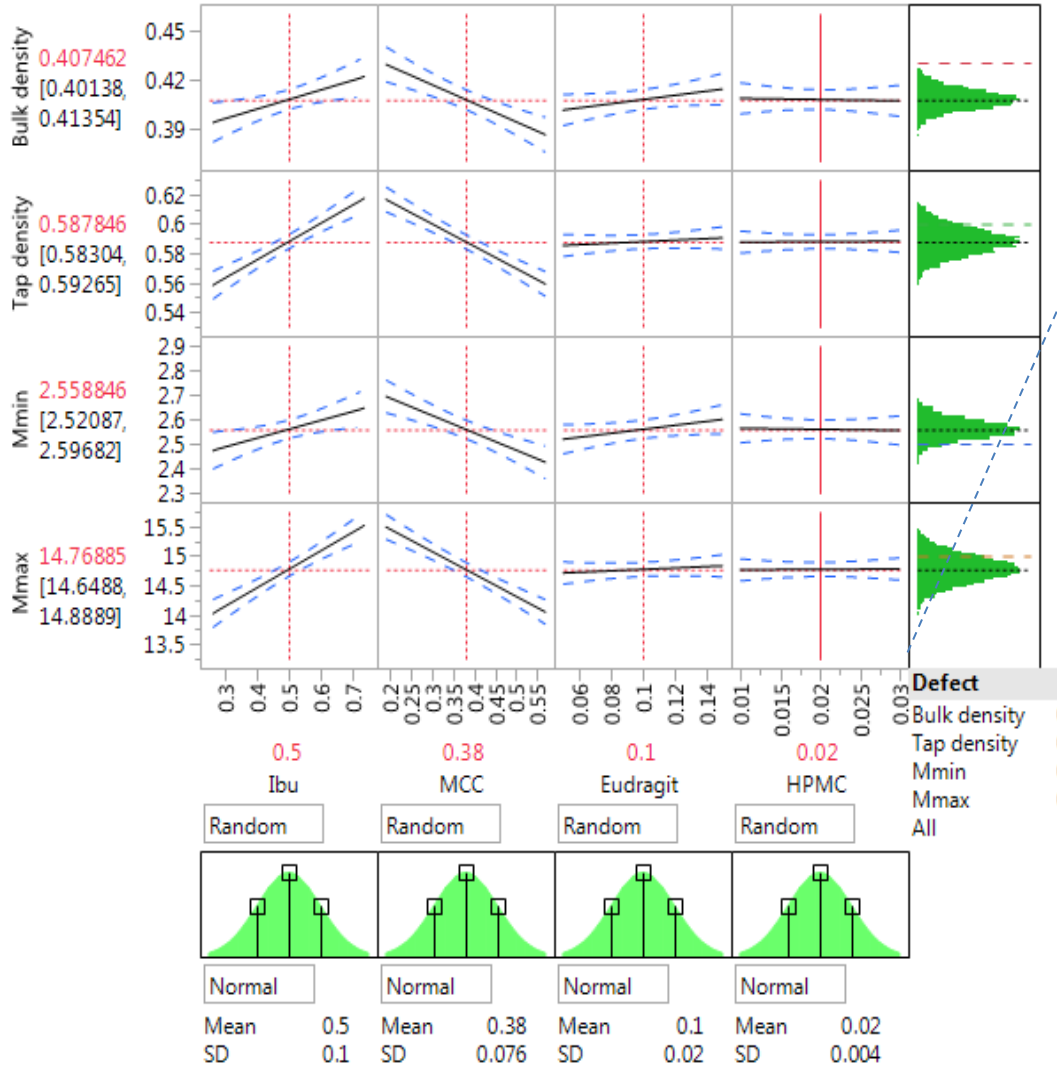
Mixture Designs

With the set up of **Ibuprofen=0.5, MCC=0.38, Eudragit=0.1 and HPMC=0.002**, and the variability structure with means at set up points and variability with normal distributions and standard deviations determined by experimental range, one gets an overall defect rate of **24%.**

The Mmax and Mmin responses generated by these simulations have respective means and standard deviations (in brackets) of 14.77 (0.34) and 2.56 (0.06). These two responses induced failure rates of 17% and 7% respectively.

In the simulation experiments, the four factors (components) were sampled independently from their specific variability distributions. JMP also makes it possible to include a correlation structure between the sampled values.

Mixture Designs



Defect	Rate	Mean	SD
Bulk density	0.0076	0.40747	0.00913
Tap density	0.1034	0.58779	0.01342
Mmin	0.0734	2.55893	0.05714
Mmax	0.1728	14.7673	0.33795
All	0.241		

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All	0.241		

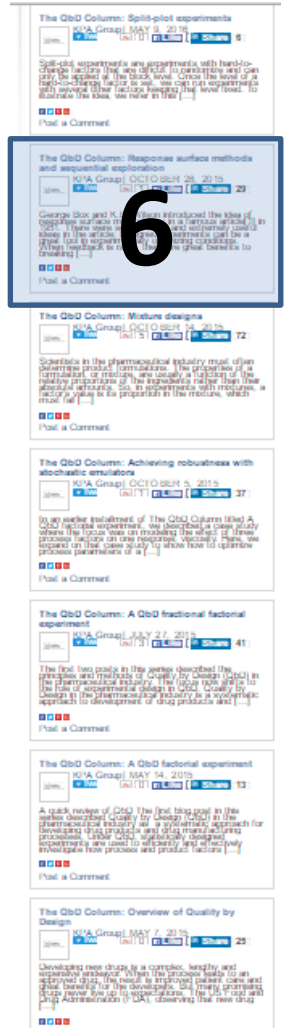
Blog 6: Sequential Exploration

The goal is to improve the drug delivery system for a class of molecules by using liposome formulations. Such formulations were expected to bring benefits by improving the ability to target the activity of the molecule in the body. However, previous efforts had yielded methods that were not commercially viable, primarily because an important critical quality attribute (CQA), encapsulation efficiency, was too low.

The experimental team focused on three CQA's in this sequence of experiments**:** **encapsulation efficiency** (with a goal of at least 20%); **particle size** (with a target range of 100-200 nm); and **storage stability** at 4^{o} C.

A risk analysis of process factors produced a list of 8 factors: lipid concentration; drug concentration; extrusion pressure; cholesterol concentration; buffer concentration; hydration time; sonication time; and number of freeze-thaw cycles.

https://community.jmp.com/t5/JMP-Blog/The-QbD-Column-Response-surface-methods-and-sequential/ba-p/30654



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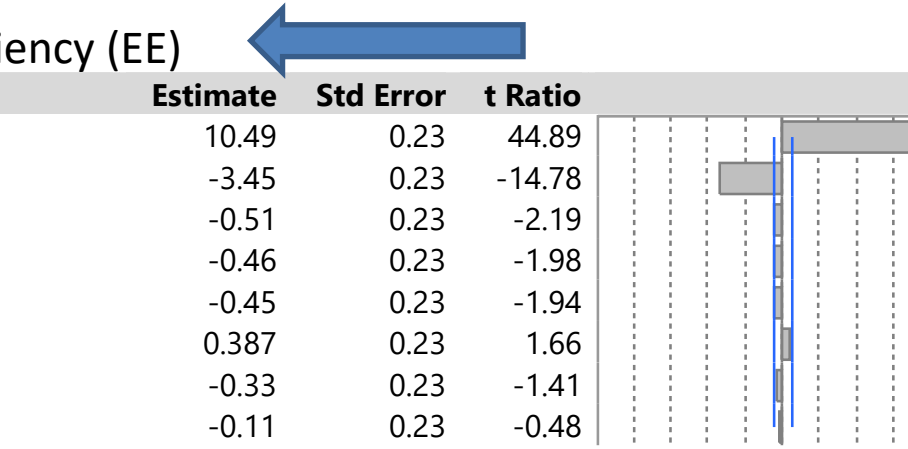
Sequential Exploration

PB Design
12+3 ctr pts

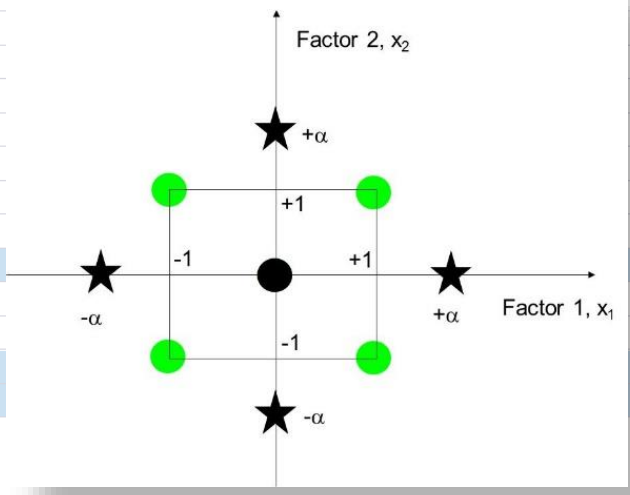
CCD Design
12

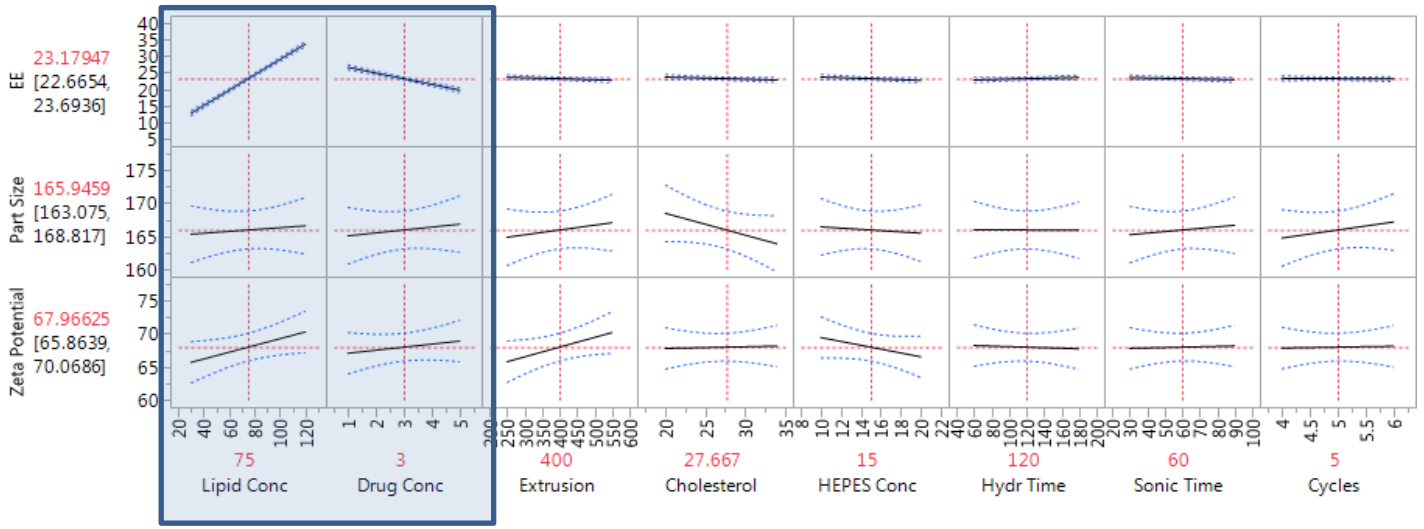
Encapsulation efficiency (EE)

Term	Estimate	Std Error	t Ratio	Prob>|t
Lipid Conc(30,120)	10.49	0.23	44.89	<.0001
Drug Conc(1,5)	-3.45	0.23	-14.78	<.0001
HEPES Conc(10,20)	-0.51	0.23	-2.19	0.071(
Extrusion(250,550)	-0.46	0.23	-1.98	0.094(
Cholesterol(20,34)	-0.45	0.23	-1.94	0.100(
Hydr Time(60,180)	0.387	0.23	1.66	0.148(
Sonic Time(30,90)	-0.33	0.23	-1.41	0.207(
Cycles(4,6)	-0.11	0.23	-0.48	0.649(



Lipid Conc	Drug Conc	Extrusion	Cholesterol	HEPES Conc	Hydr Time	Sonic Time	Cycles
30	1	250	20	10	60	30	4
120	1	250	20	20	60	90	6
120	5						4
120	5						6
120	1						4
30	5						6
30	5						4
120	1						6
120	5						4
30	5						6
75	3						5
30	1						6
30	1						4
75	3						5
75	3						5





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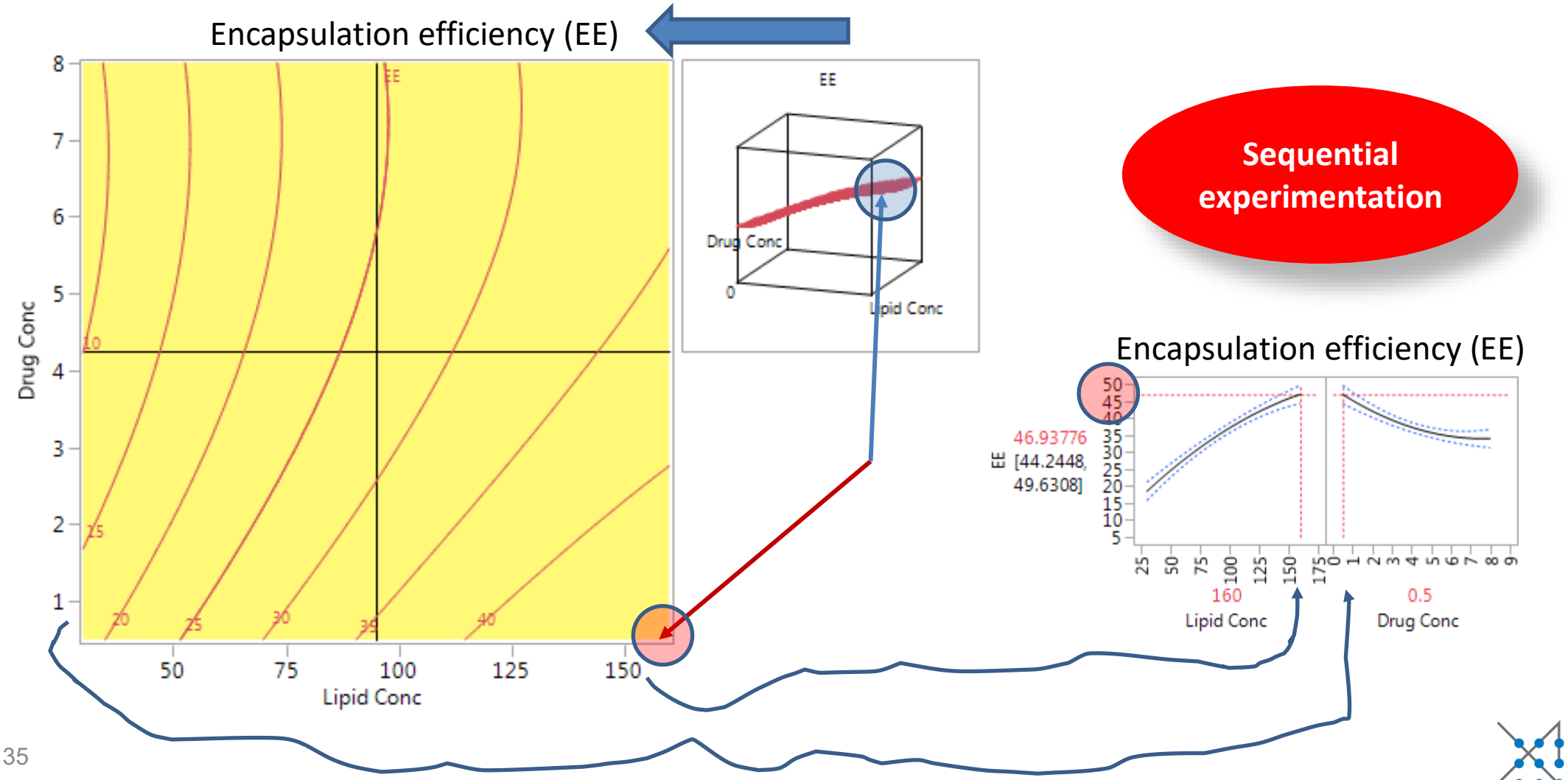
Sequential Exploration



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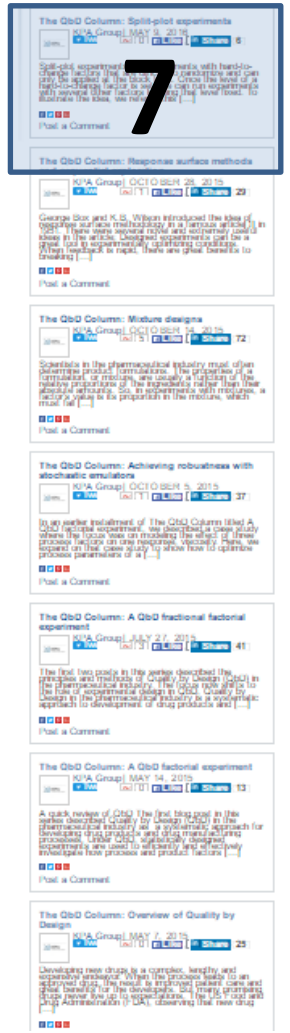
Blog 7: Split-plot Experiments

The experiment compared, on animal models, several methods for the treatment of severe chronic skin irritations. Each treatment involved an orally administered antibiotic along with a cream that is applied topically to the affected site. There were **two types of antibiotics, and the cream was tested at four concentrations and three timing strategies**.

The experiment was run using four experimental animals, each of which had eight sites located on their backs from the neck down. Thus, the sites are "blocked" by animal. For each animal, we can randomly decide which sites should be treated with which concentration by timing option. The antibiotics are different. They are taken orally, so each animal could get just one antibiotic, and it would then apply to all the sites on that animal.

https://community.jmp.com/t5/JMP-Blog/The-QbD-Column-Split-plot-experiments/ba-p/30716



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Split-plot Experiments

Effective treatment combinations will have low values of AUC. There is a clear effect associated with concentration (p-value=0.002). The effect for timing has a p-value of 0.076. The F-statistic for comparing the two antibiotics is larger than the one for timing. However, it has a p-value of 0.078, close to the one for timing.

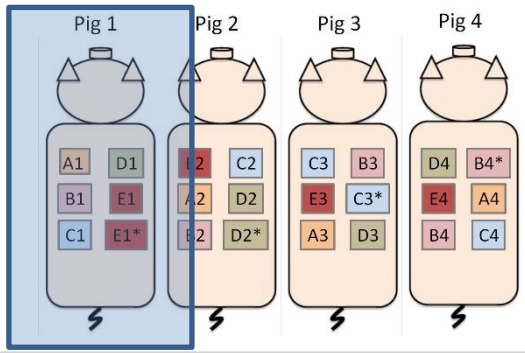
The reason is that the antibiotic comparison is at the “whole plot” level and so has more uncertainty, and much lower power, than the comparisons of timing strategies and concentrations.

The topical cream study provided valuable information that the cream is more effective at higher concentrations.

The use of multiple sites per animal permitted “within animal” comparisons of the concentrations and timing, so that the positive effect of increasing concentration could be discovered with a small number of animals. **The “between animal” variation was only about 1/3 as large as the “within animal variation**.” This was a surprise, as we had expected that there would be substantial inter-animal variation.

Analysis of Random Effects

Hard to change (HTC) factors



Factors

Add Factor | Remove | Add N Factors 1

Name	Role	Changes	Values
Antibiotic	Categorical	Hard	A B
Timing	Categorical	Easy	2 4 12
Concentration	Categorical	Easy	0 2 4 6

Design

Run	Whole Plots	Antibiotic	Timing	Concentration
1	1	B	4	4
2	1	B	4	6
3	1	B	4	2
4	1	B	12	2
5	1	B	12	0
6	1	B	2	4
7	1	B	2	6
8	1	B	2	0
9	2	A	2	2
10	2	A	12	0
11	2	A	12	6
12	2	A	4	0
13	2	A	12	4
14	2	A	2	4
15	2	A	2	6
16	2	A	4	2
17	3	B	4	6
18	3	B	4	2
19	3	B	12	6
20	3	B	2	4
21	3	B	12	4
22	3	B	2	0
23	3	B	4	0
24	3	B	2	2
25	4	A	12	2
26	4	A	4	4
27	4	A	12	0
28	4	A	2	2
29	4	A	4	6
30	4	A	2	6
31	4	A	2	0
32	4	A	12	4

REML Variance Component Estimates

Random Effect	Var Ratio	Var Component	Std Error	95% Lower	95% Upper	Pct of Total
Animal	0.3369366	0.0009742	0.0014479	-0.001864	0.003812	25.202
Residual		0.0028914	0.0011798	0.0014872	0.0078735	74.798
Total		0.0038656	0.0017459	0.0018763	0.0120769	100.000

-2 LogLikelihood = 5.203110

Note: Total is the sum of the positive variance components.

Total including negative estimates = 0.0038656

Fixed Effect Tests

Source	Nparm	DF	DFDen	F Ratio	Prob > F
Antibiotic	1	1	1.82	13.1960	0.0783
Timing	2	2	12.01	3.2182	0.0760
Concentration	3	3	12.06	9.2033	0.0019*
Antibiotic*Timing	2	2	12.01	0.3831	0.6898
Antibiotic*Concentration	3	3	12.03	0.7022	0.5687
Timing*Concentration	6	6	12.47	0.6574	0.6849

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https://community.jmp.com/t5/Discovery-Summit-Europe-2021/Maximizing-Data-Science-Success-with-Information-Quality-InfoQ/ta-p/349217

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https://community.jmp.com/t5/JMP-Blog/Analytic-work-in-Industry-4-0-applications-A-checklist/ba-p/264864

Analytic work in Industry 4.0 applications: A checklist

Created: MAY 6, 2020 12:59 PM

Consider this hypothetical: You work for a company developing and manufacturing medical devices. The COVID-19 pandemic created a worldwide shortage of ventilators. Since your company has recently implemented a major digital transformation strategy to meet Industry 4.0 standards, you are able to predict operating failures in alternative assembly lines, provide online monitoring of wave soldering processes, and gather focused statistics on assembly defects from automated visual inspection robots.

The flexibility acquired by this digital transformation permitted the rapid conversion of the company's production lines to make the much-needed mechanical ventilators. A major element in this transformation is the application of analytics, since the flexibility described above requires high-level analytic capabilities. Keep reading for additional background and a checklist for reviewing analytic-based

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The Checklist

These are the eight questions to ask when reviewing an analytic study after clarifying the goals and utility.

Dimension	*Questions*
Data resolution	Is the data granularity adequate for the intended job? Has measurement uncertainty been evaluated and found appropriate?
Data structure	Is it possible to use data from different sources that reflect on the problem at hand?
Data integration	How is data from different sources integrated? Are there linkage issues that lead to dropping crucial information?
Temporal relevance	Does the time gap between data collection and analysis cause any concern?
Chronology of data and goal	Are the analytic findings communicated to the right persons in a timely manner?
Generalizability	Can general conclusions be derived beyond what was explicitly studied? For example, conclusions that can be applied to other products or processes.
Operationalization	Are the measured variables themselves relevant to the study goal? Are there any stated action item recommendations derived from the study?
Communication	Are findings properly communicated to the intended audience?

https://community.jmp.com/t5/JMP-Blog/Analytic-work-in-Industry-4-0-applications-A-checklist/ba-p/264864

Is your work generating information quality?

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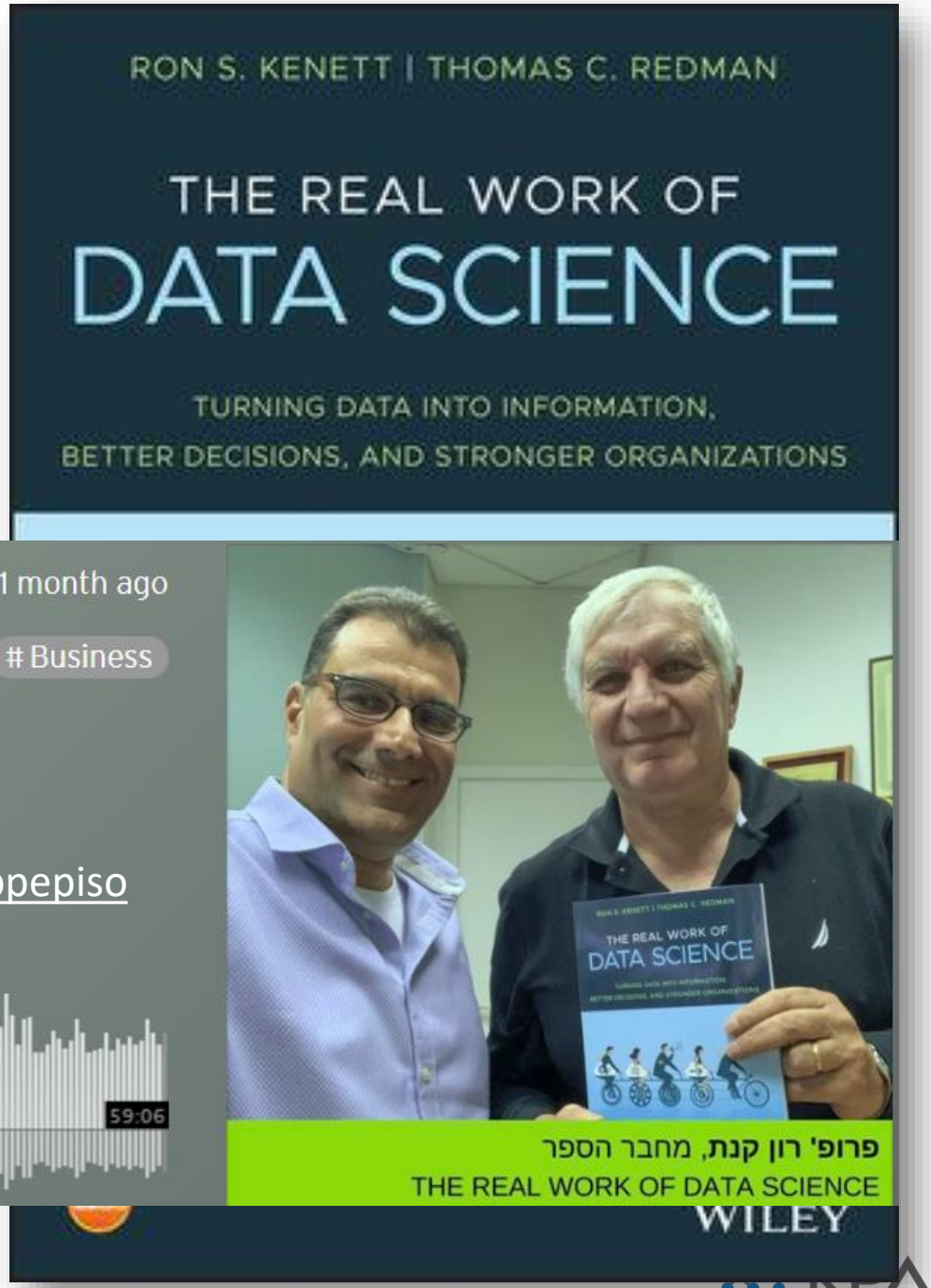
Research Article | Open Access

Helping reviewers assess statistical analysis: A case study from analytic methods

Ron S. Kenett, Bernard G. Francq

https://chemistry-europe.onlinelibrary.wiley.com/doi/full/10.1002/ansa.202000159



https://www.youtube.com/watch?v=oHn-jXHm46c

Thank you for your attention