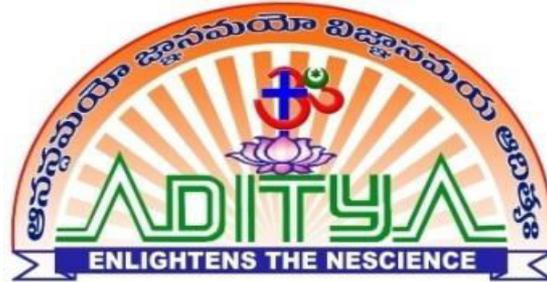


EXPERIMENT DESIGN PROCESS



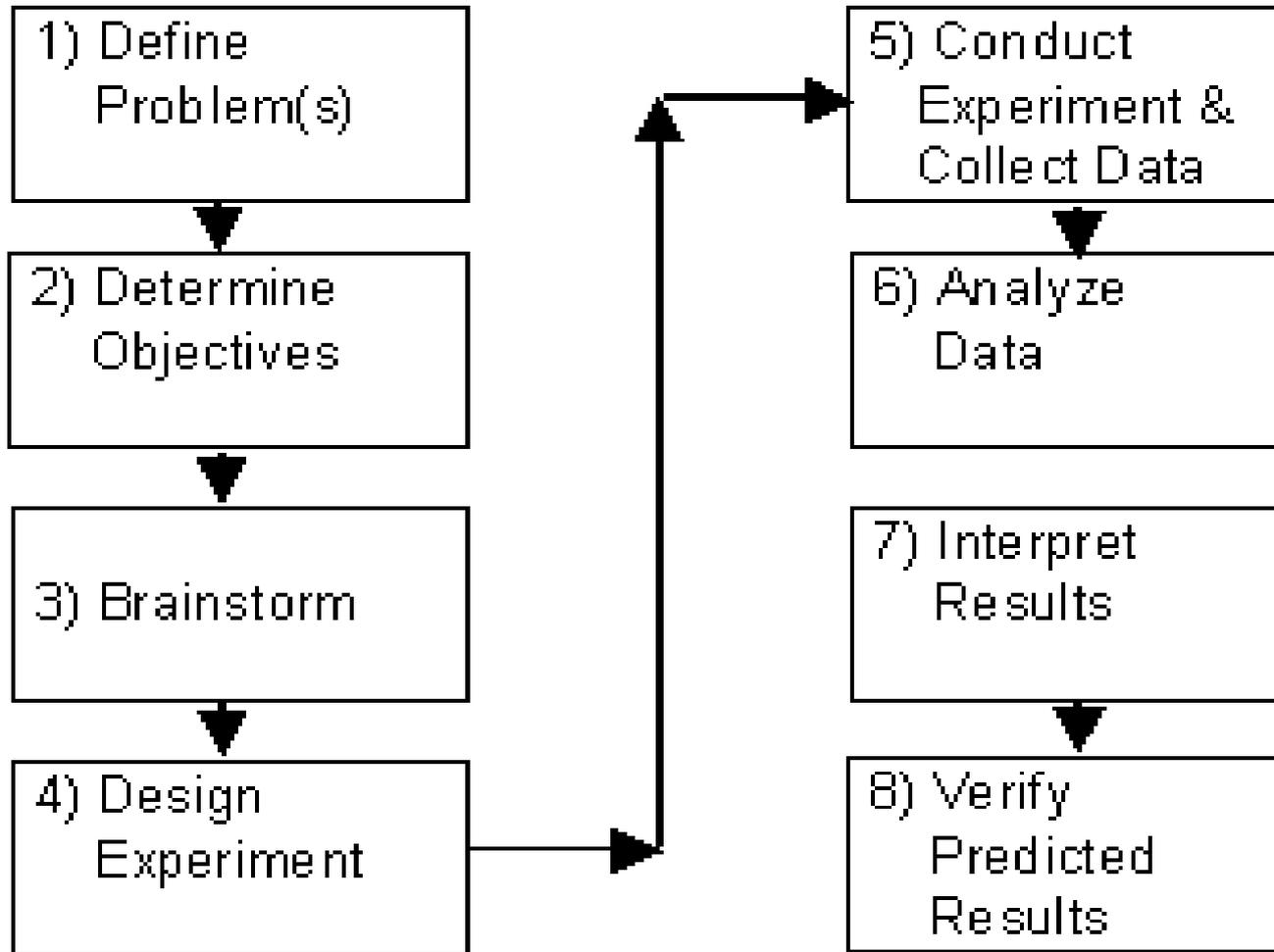
ADITYA PHARMACY COLLEGE



"There's a flaw in your experimental design.
All the mice are scorpions."

PRESENTED BY:
G.SRIDEVI
Emp ID: 2940
M.PHARMACY I-II SEM
SUBJECT: FDPC

- EXPERIMENT DESIGN PROCESS:



TYPES OF DOE:

- o One Factorial
- o Full Factorials
- o Fractional Factorials
- o Screening Experiments
- o Plackett-Burman Designs
- o Taguchis Orthogonal Arrays
- o Response Surface Analysis

ONE FACTORIAL METHOD:

- One factorial experiments look at **only one factor having an impact on** output at different factor levels.
- The factor can be qualitative or quantitative.
- In the case of qualitative factors (e.g. different suppliers, different materials, etc.), no predictions can be performed outside the tested.
- Each level of the factor is investigated to see if the response is significantly different from the response at other levels of the factor.

FULL FACTORIAL METHOD: Full factorial experiments look **completely at all factors included in the** experimentation.

- In full factorials, all of the possible combinations that are associated with the factors and their levels are studied.
- The effects that the main factors and all the interactions between factors are measured.
- If we use more than two levels for each factor, we can also study whether the effect on the response is linear or if there is curvature in the experimental region for each factor and for the interactions.

Full factorial experiments can require many experimental runs if many factors at many levels are investigated.

2. FACTORIAL METHOD: The simplest of the two level factorial experiments is the design where two factors (say factor A and factor B) are investigated at two levels. A single replicate of this design will require four runs.

Consider 2 factors A & B, so there will be 4 combinations (2^2) Say, 2 levels each Hi (+1) and low(-1)

So the possible combinations are illustrated in the below table:

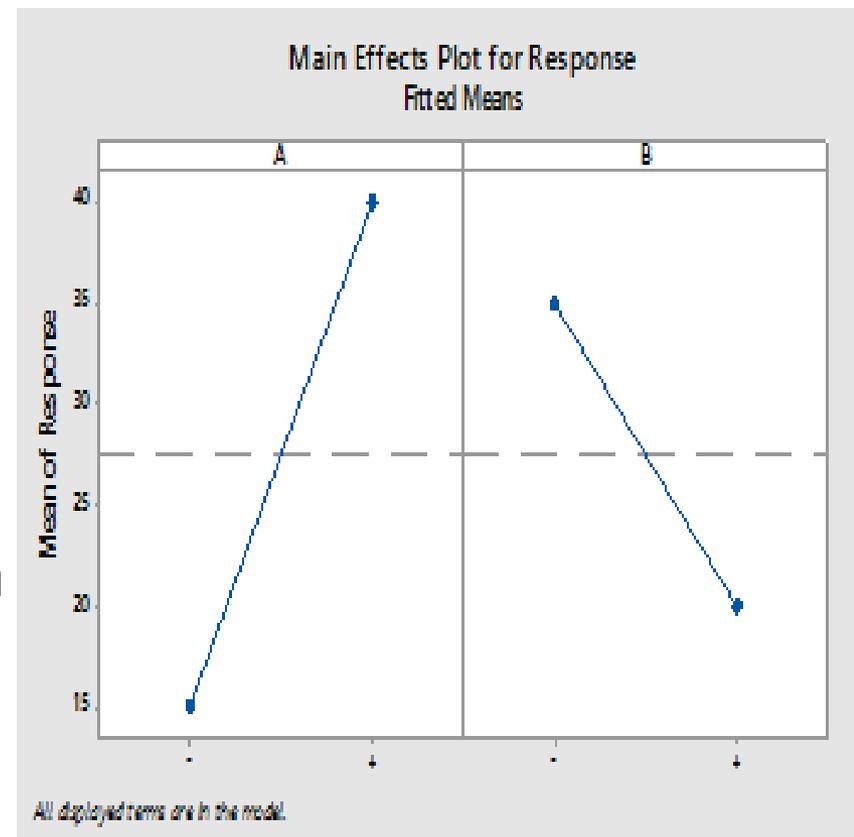
Run #	A	B	Response
1	+	+	30
2	+	-	50
3	-	+	10
4	-	-	20

Main effect of A

= Mean response at+ level – Mean response at – level = $(30+50)/2 - (10+20)/2 = 40 - 15 = 25$

Main effect of B

= Mean response at+ level – Mean response at – level = $(30+10)/2 - (50+20)/2 = 20 - 35 = -15$

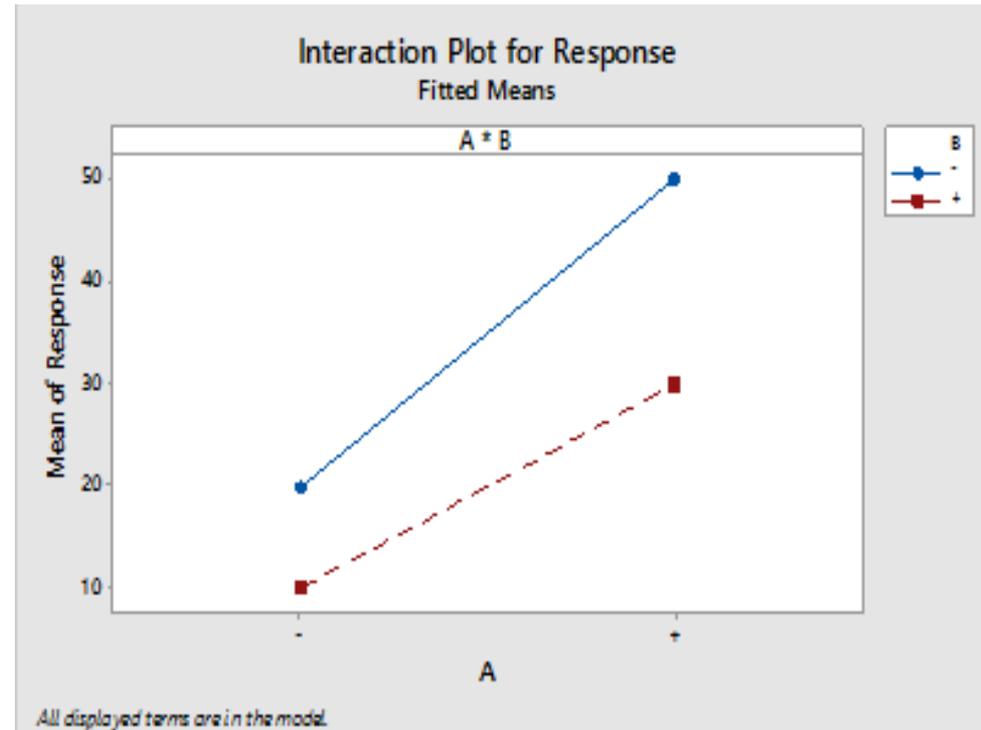


2 FACTORIAL METHOD:

Run #	A	B	Response
1	+	+	30
2	+	-	50
3	-	+	10
4	-	-	20

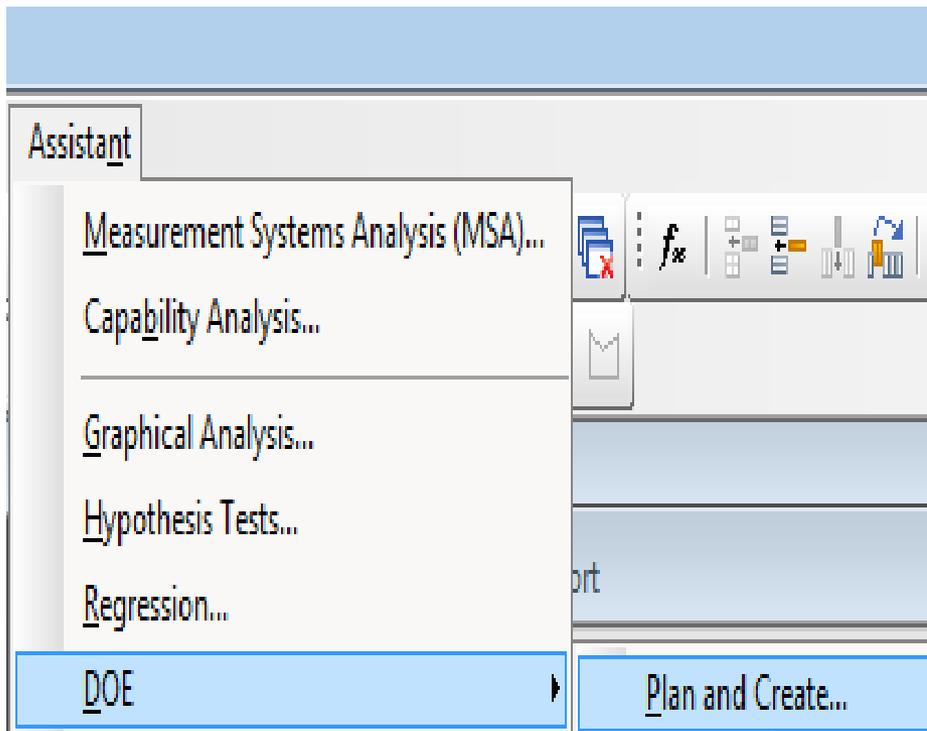
Interaction effect of A*B
= Mean response at+ level –
Mean response at -level
= $(30+20)/2 - (50+10)/2 = 25$
– 30 = -5

Interaction is obtained by
multiplying the factors
involved

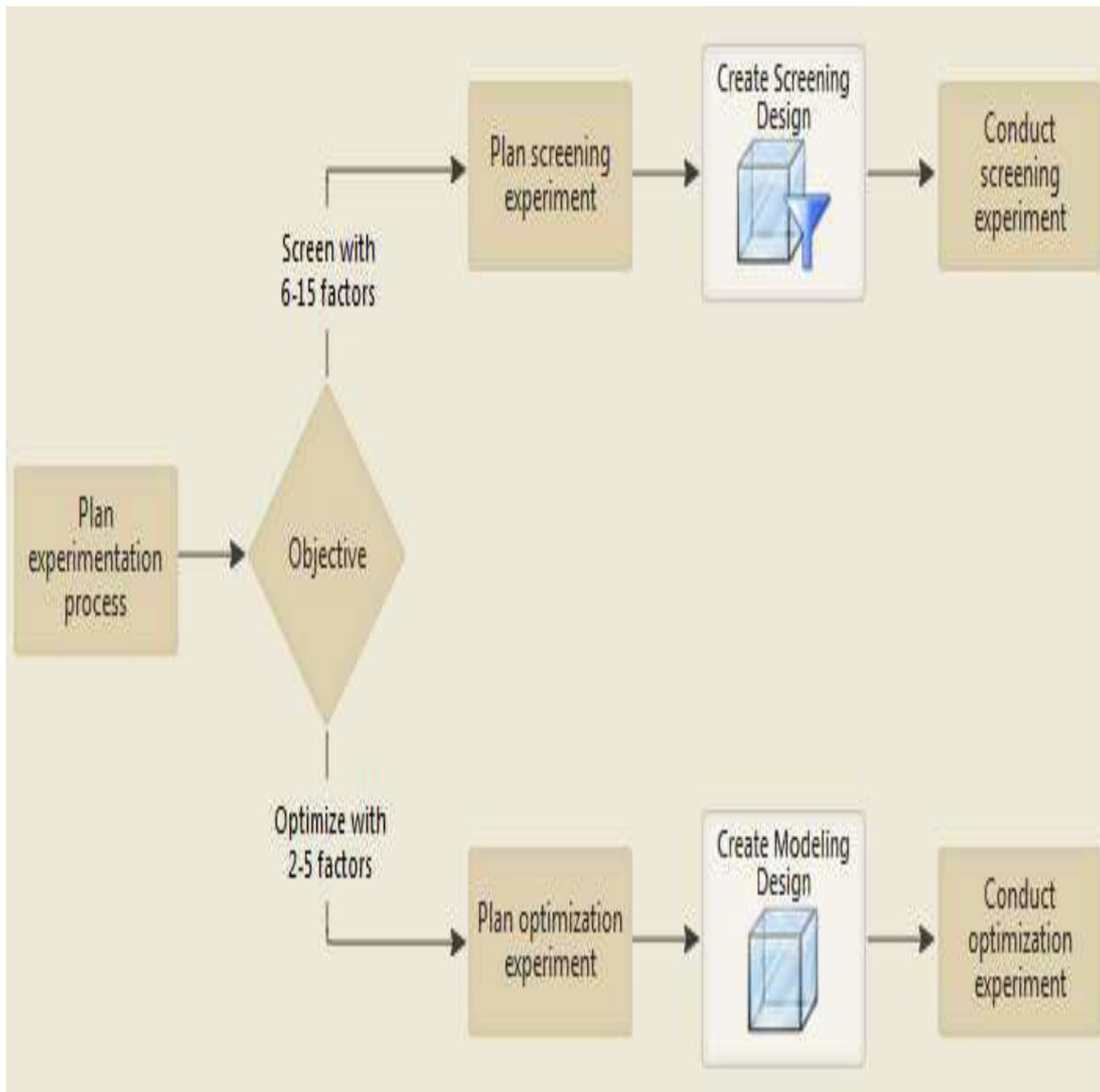


Run #	A	B	Response
1	+	+	33
2	+	-	56
3	-	+	16
4	-	-	26

EXAMPLE:



- Go to Standard tool Bar
- Move cursor to **DOE**
- Select **Plan and**
- **Create**



From below
popup

select **Create
Modeling Design**
(as

we are dealing
with 2

factors for now)

Response

Enter the name of your response variable:

Response

What is your response goal?

None

Factors

Number of factors:

2

Enter your factor names and settings:

Name	Type	Low	High
Trns per day	Continuous	8	78
Pross per dy	Continuous	3	6

Replicates

Adding replicates allows you to detect smaller effect sizes.

Number of replicates:

4

Number of runs

Total number of center points in your design: 6

Total number of runs in your design: 22

OK

Cancel

- Enter the Name of the Response Variable (or leave as is as **Response**)
- Select the **Goal**
- Select Factors as **2**
- Enter **Factor Names and Settings**
- Enter the No. of replicates (here it is 4)
- No. of runs auto populate based on factors and replicates

Create Modeling Design Summary Report

Experimental Goal

Construct a model that describes the relationship between the response and critical factors. If the model is adequate, use it to find optimal settings for the factors.

Design Information

Response Goal	Response Not specified
Base design	2 factors, 4 runs
Replicates	4
Center points	6
Total runs	22

Replicate pairs are placed in separate blocks.

Factors and Settings

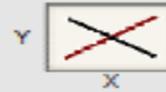
Factor	Low	High
Trns per day	8	78
Pross per dy	3	6

Effect Estimation

This design will estimate all linear main effects and two-way interactions.



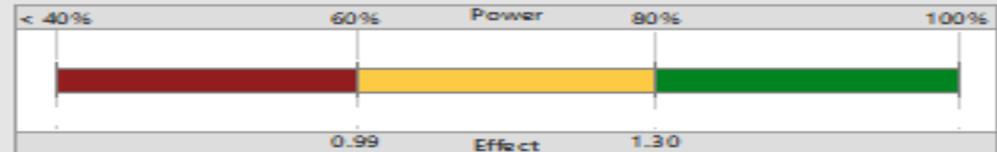
Main effect: Describes how the response (Y) changes if you change the setting of one factor (X).



Interaction: Describes how the response (Y) changes if you change the settings of two factors (X).

Detection Ability

What effect sizes can you detect with this 4-replicate design?



You have an 80% chance of detecting effects of 1.30 standard deviations or more. With 6 replicates, you can detect effects of 1.04.



- Modeling Design, Graph would appear with below details
- Experimental Goal, Design Information Factors and Settings
- Effect Estimation , Detection Ability

C1	C2	C3	C4	C5	C6	C7 
StdOrder	RunOrder	CenterPt	Blocks	Trns per day	Pross per dy	Response
22	4	0	2	43	4.5	98
14	5	1	2	8	6.0	53
20	6	0	2	43	4.5	67
13	7	1	2	78	3.0	88
18	8	1	2	8	6.0	65
12	9	1	2	8	3.0	70
16	10	1	2	8	3.0	82
17	11	1	2	78	3.0	99
9	12	0	1	43	4.5	87
8	13	1	1	78	6.0	67
4	14	1	1	78	6.0	54
2	15	1	1	78	3.0	83
7	16	1	1	8	6.0	97
1	17	1	1	8	3.0	65
3	18	1	1	8	6.0	72
5	19	1	1	8	3.0	89
6	20	1	1	78	3.0	91
10	21	0	1	43	4.5	79
11	22	0	1	43	4.5	67

- Enter your responses
- in Response column (C7)

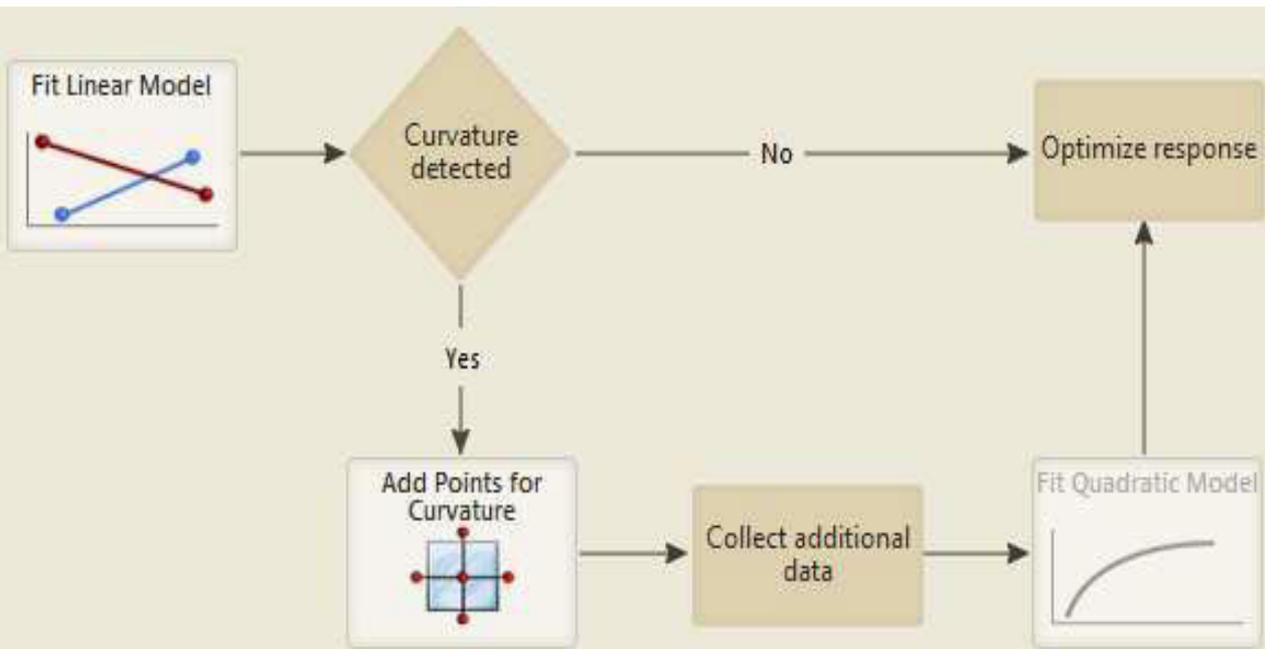
Assistant

- Measurement Systems Analysis (MSA)...
- Capability Analysis...
- Graphical Analysis...
- Hypothesis Tests...
- Regression...
- DOE**
- Before/After Capability Analysis...



- Plan and Create...
- Analyze and Interpret...**

Go to Standard tool Bar
Move cursor to **DOE**
Select **Analyze and Interpret**



From below popup select **Fit Liner Model**

Fit Linear Model

Minitab will fit a linear model between the response and the critical factors. Using the response goal below, Minitab will find settings for the factors that best satisfy the goal if the model is appropriate.

Response Goal

Response variable: Response

What is your response goal? **Minimize the response**

OK

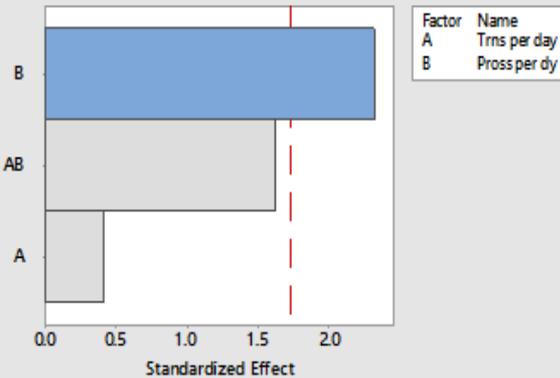
Cancel

From below popup
select **Minimize the response** and click **OK**

Fit Linear Model for Response Summary Report

Pareto Chart of Standardized Effects

Terms with longer bars have more influence on Response.



Design Information

Base design	2 factors, 4 runs
Replicates	4
Center points	6
Total runs	22
Blocks	2

Optimal Factor Settings

Factor	Setting	Predicted Y
Pross per dy	6	69.625

Comments

You can conclude that there is a relationship between Response and the factors in the model at the 0.10 level of significance.

The blue bars in the Pareto chart represent the terms that are included in the model.

Your goal is to minimize Response. Using the optimal settings for the factors included in the model, the predicted value of Response is 69.625.

The model explains 21.20% of the variation in Response.

% of variation explained by the model



21.20% of the variation in Response can be explained by the model.

summary Report

you can identify signifying factors

from Pareto chart Here it is B i.e.,Processors per day has more impact than no. of transactions

per day on Quality scores % of Variation

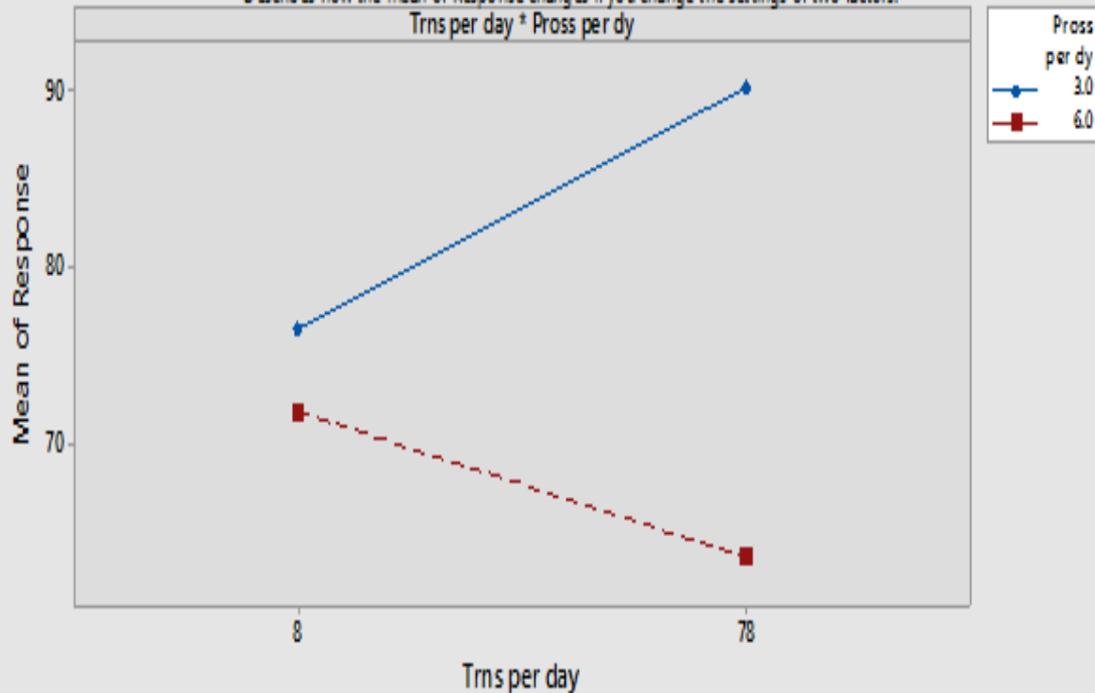
design info Optimal factor setting

Fit Linear Model for Response Effects Report

Interaction Plots for Response

Describes how the mean of Response changes if you change the settings of two factors.

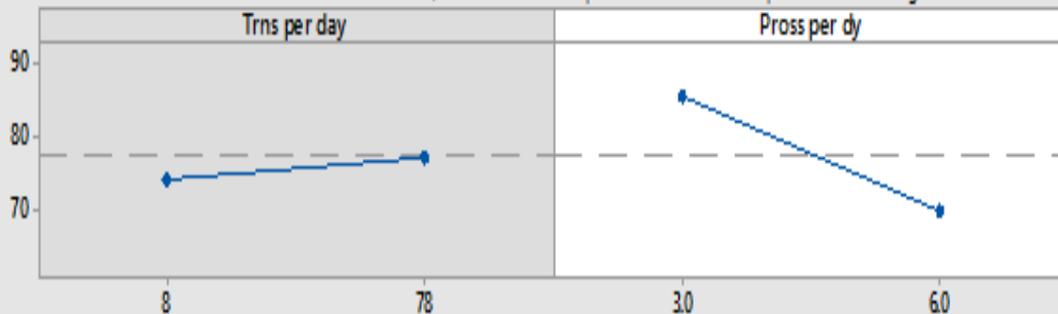
Trns per day * Pross per dy



Main Effects Plots for Response

Describes how changes to a single factor affect the mean of Response.

If there is an interaction between factors, use the interaction plots to determine the optimal factor settings.



A gray background represents a term that was removed from the model because it is not statistically significant.

From below chart we can understand the Main effect and Interaction effect

- It shows, transactions per day has less significant compared to Processors per day
- The AB interaction plot also nearly significant

Fractional Factorial method:

- Fractional factorials look at **more factors with fewer runs**.
- Using a fractional factorial involves making a major assumption – that higher order interactions (those between three or more factors) are not significant.
- Fractional factorial designs are derived from full factorial matrices by substituting higher order interactions with new factors.
- To increase the efficiency of experimentation, fractional factorials give up some power in analyzing the effects on the

response. Fractional factorials will still look at the main factor effects, but they lead to compromises when looking into interaction effects. This compromise is called confounding.

Screening Experiments:

Screening experiments are the ultimate fractional factorial experiments.

These experiments assume that all interactions, even two-way interactions, are not significant.

They literally screen the factors, or variables, in the process and determine which are the critical variables that affect the

process output.

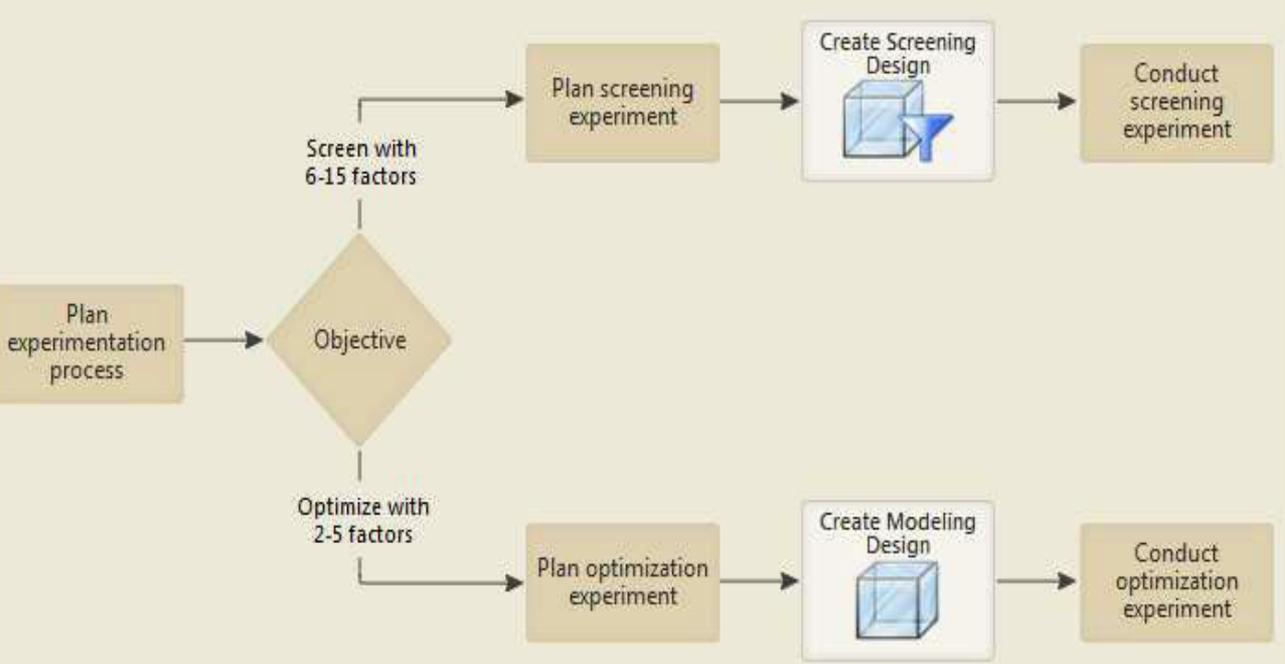
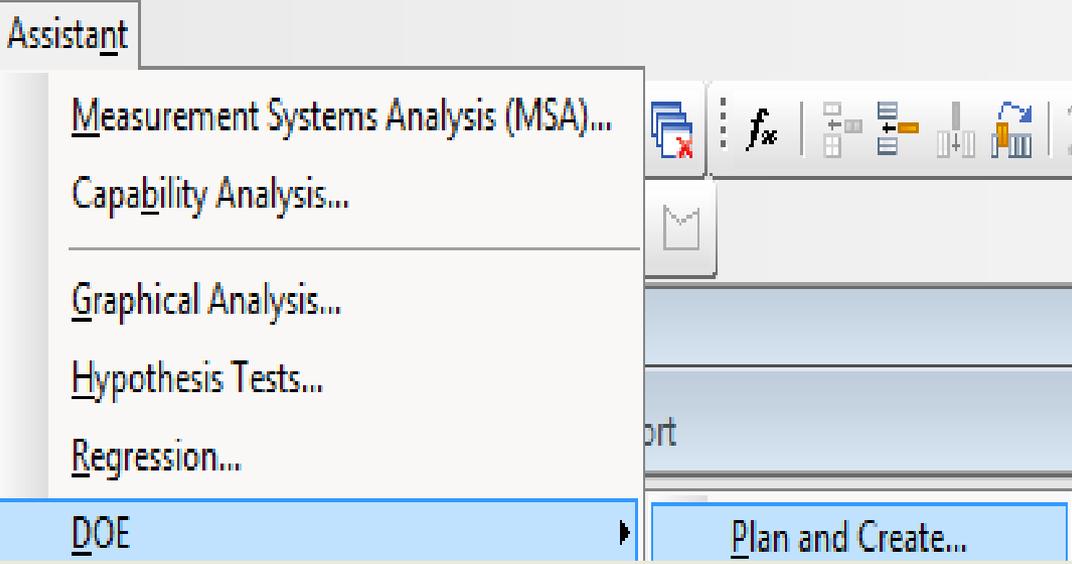
There are two major families of screening experiments:

Drs. Plackett and Burman developed the original family of screening experiments matrices in the 1940s.

Dr. Taguchi adapted the Plackett–Burman screening designs. He modified the Plackett–Burman design approach so that the experimenter could assume that interactions are not significant, yet could test for some two-way interactions at the same time.

Example:

Go to Standard tool Bar
Move cursor to **DOE**
Select **Plan and Create**



From below popup
select (Screen with 6 -
15 factors) **Create
Screening Design** (as
we are dealing with 6
factors for now)

Create Screening Design

Response and factors

Enter the name of your response variable:

Number of factors:

Enter your factor names and settings:

Name	Type	Low	High
Experience	Continuous	1	10
Shift	Continuous	1	3
Education	Categorical	UG	PG
Transactions	Continuous	10	50
Gender	Categorical	A	B
Age	Continuous	25	40

Number of runs

Adding runs allows you to detect smaller effect sizes.

Total number of runs in your design:

OK Cancel

Enter the Name of the Response Variable (or leave as is as **Response**)

Select Factors as **6**

Enter **Factor Names and Settings**

Select the No. of runs

Click **OK**

Create Screening Design Summary Report

Experimental Goal

Reduce the number of factors down to the critical few that have the greatest influence on the response.

Effect Estimation

This design will estimate the linear main effects for all factors. Interactions will not be estimated with this design.



Main effect: Describes how the response (Y) changes if you change the setting of one factor (X).

Design Information

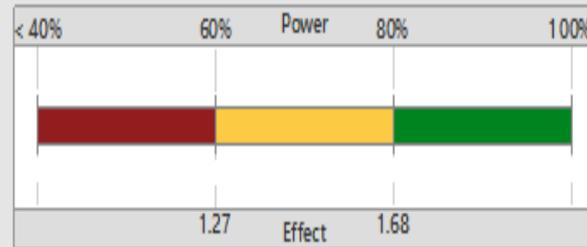
Response	Response
Base design	6 factors, 12 runs
Total runs	12

Factors and Settings

Factor	Low	High
Experience	1	10
Shift	1	3
Transactions	10	50
Age	25	40
Education	UG	PG
Gender	A	B

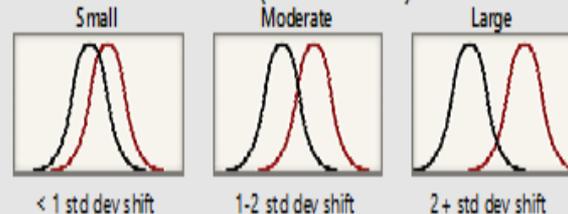
Detection Ability

What effect sizes can you detect with this 12-run design?



With 12 runs, you have an 80% chance of detecting effects of 1.68 standard deviations or more. With 24 runs, you can detect effects of 1.06.

Effect Size (Shift in the Mean)



Modeling Design

Graph would appear

with below details

Experimental Goal

Design Information

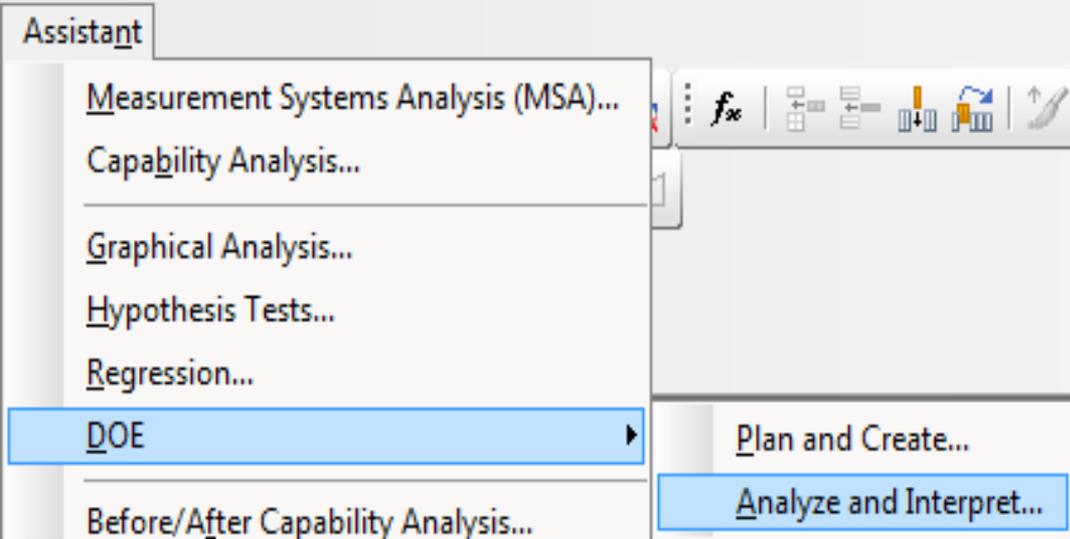
Factors and Settings

Effect Estimation

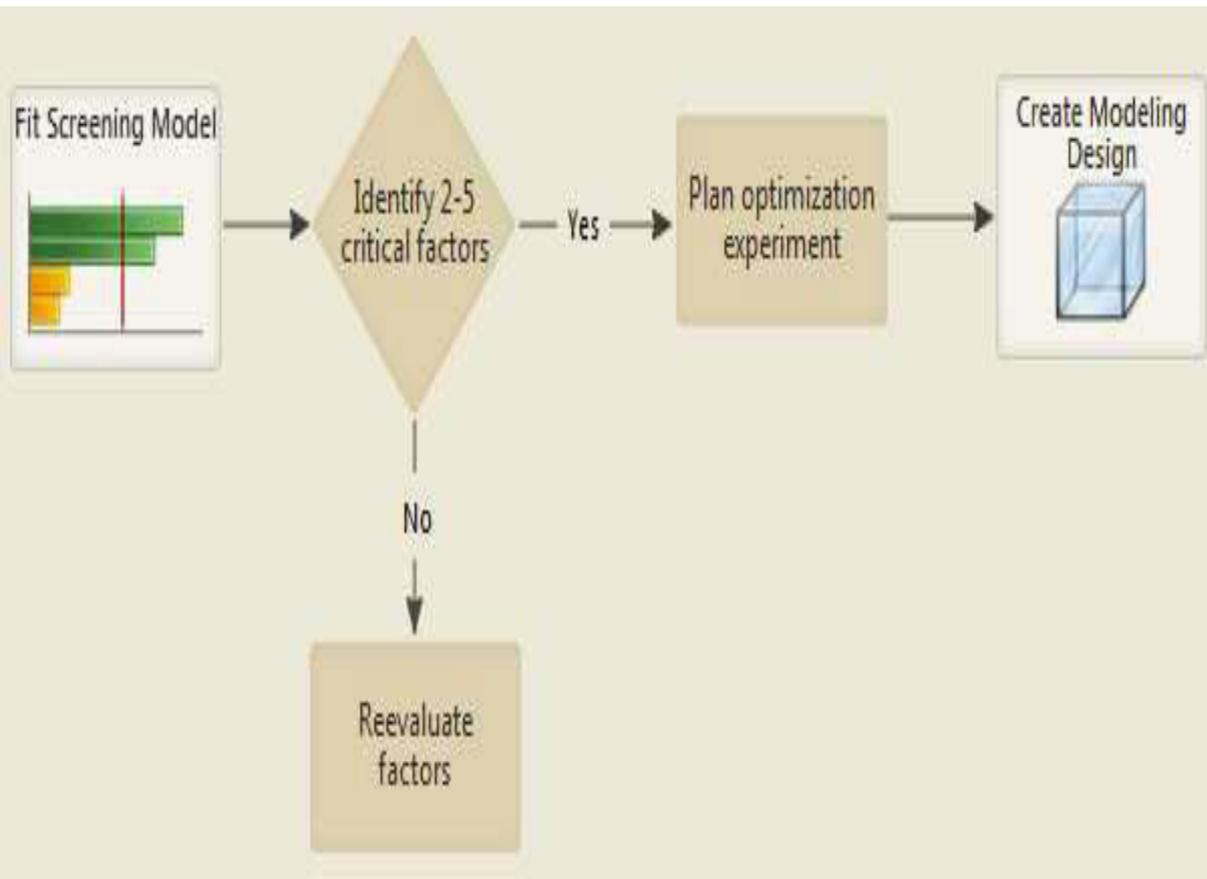
Detection Ability

C1	C2	C3	C4	C5	C6	C7	C8	C9-T	C10-T	C11
StdOrder	RunOrder	PtType	Blocks	Experience	Shift	Transactions	Age	Education	Gender	Response
1	1	1	1	10	1	50	25	UG	A	66
9	2	1	1	1	1	10	40	PG	B	82
5	3	1	1	10	3	10	40	PG	A	62
10	4	1	1	10	1	10	25	PG	B	71
6	5	1	1	10	3	50	25	PG	B	60
8	6	1	1	1	1	50	40	PG	A	91
3	7	1	1	1	3	50	25	PG	A	70
12	8	1	1	1	1	10	25	UG	A	97
11	9	1	1	1	3	10	25	UG	B	56
2	10	1	1	10	3	10	40	UG	A	72
4	11	1	1	10	1	50	40	UG	B	91
7	12	1	1	1	3	50	40	UG	B	73

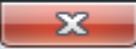
Enter your responses in Response column (C11), Quality scores



Go to Standard tool Bar
Move cursor to **DOE**
Select **Analyze and Interpret**



From below popup
select **Fit Screening Model**



Fit screening model?

The recommended next step is to fit a screening model to your data. This will help you reduce the current list of potential factors down to a critical few.

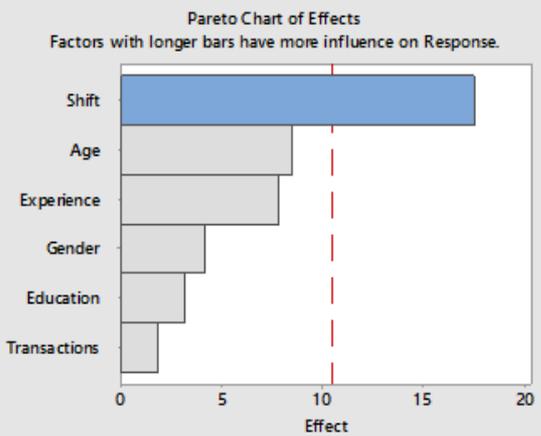
Do you want to fit a screening model?

Yes

No

From below popup select **Yes**

Fit Screening Model for Response Summary Report



Design Information

Base design	6 factors, 12 runs
Total runs	12

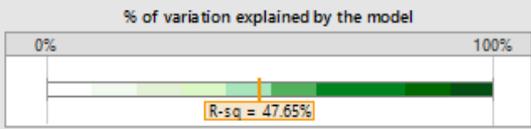
The red line is the effect size at the 0.10 level of significance. Gray bars represent non-significant factors that were removed from the model.

Comments

You can conclude that 1 of the factors in your model is significant at the 0.10 level of significance.

The blue bars in the Pareto chart represent the significant factors that are included in the model. Evaluate the size of the effects to determine whether they have practical implications.

The model explains 47.65% of the variation in Response.



47.65% of the variation in Response can be explained by the model.

summary Report

you can identify signifying factors

from Pareto chart

Here it is Shift i.e.,

shift has more impact on

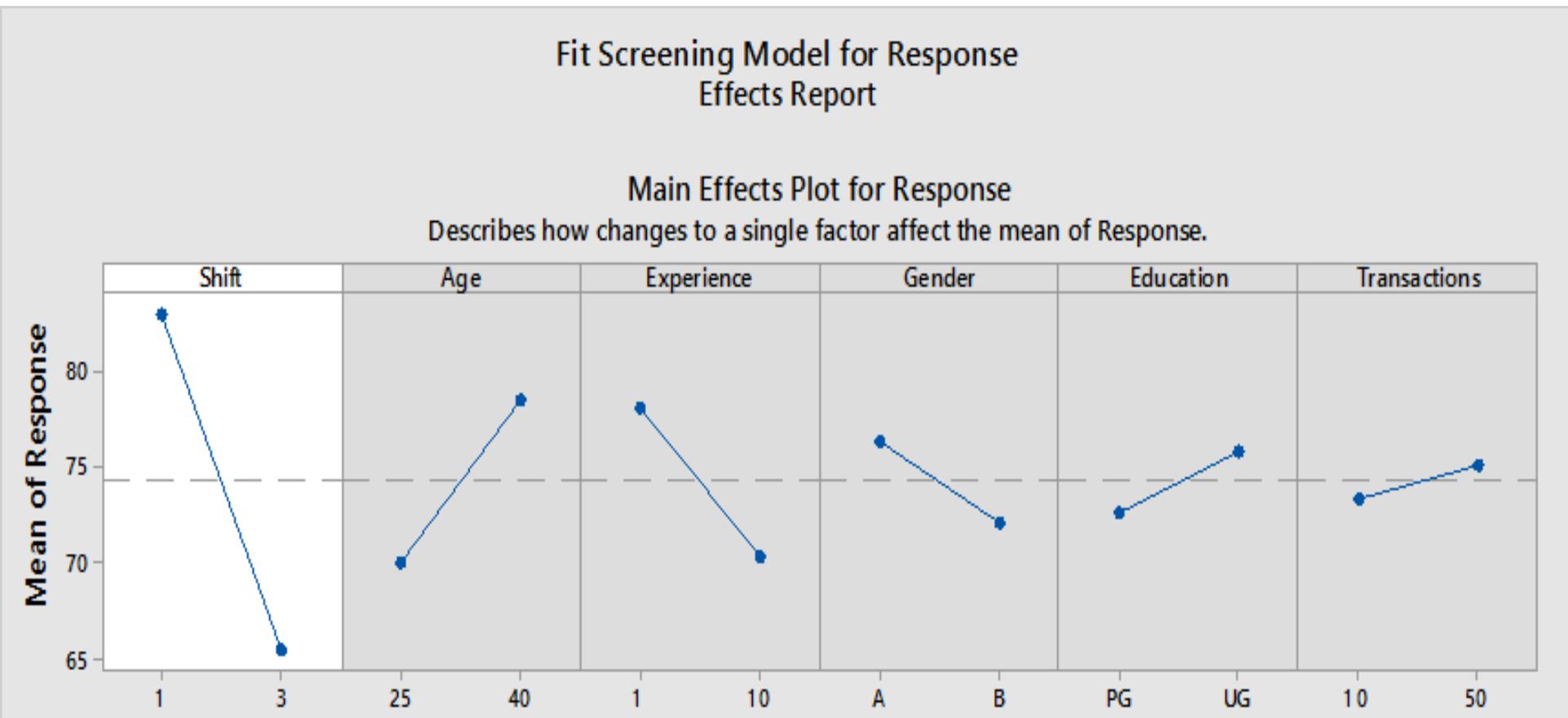
Quality

Scores % of Variation design info

From below chart we can understand the Main effect

It shows, Shift of day has higher impact on Quality score

The Factors shown in gray background are statistically insignificant and can be ignored from analysis.



Response Surface Analysis (RSM):

RSM explores the relationships between several explanatory variables and one or more response variables.

The method was introduced by G. E. P. Box and K. B. Wilson in 1951.

The main idea of RSM is to use a sequence of designed experiments to obtain an optimal response.

Response surface analysis is an off-line optimization technique.

Usually, 2 factors are studied; but 3 or more can be studied.

With response surface analysis, we run a series of full factorial experiments and map the response to generate mathematical equations that describe how factors affect the response.



THANK YOU

I FOLLOW YOU

YOU