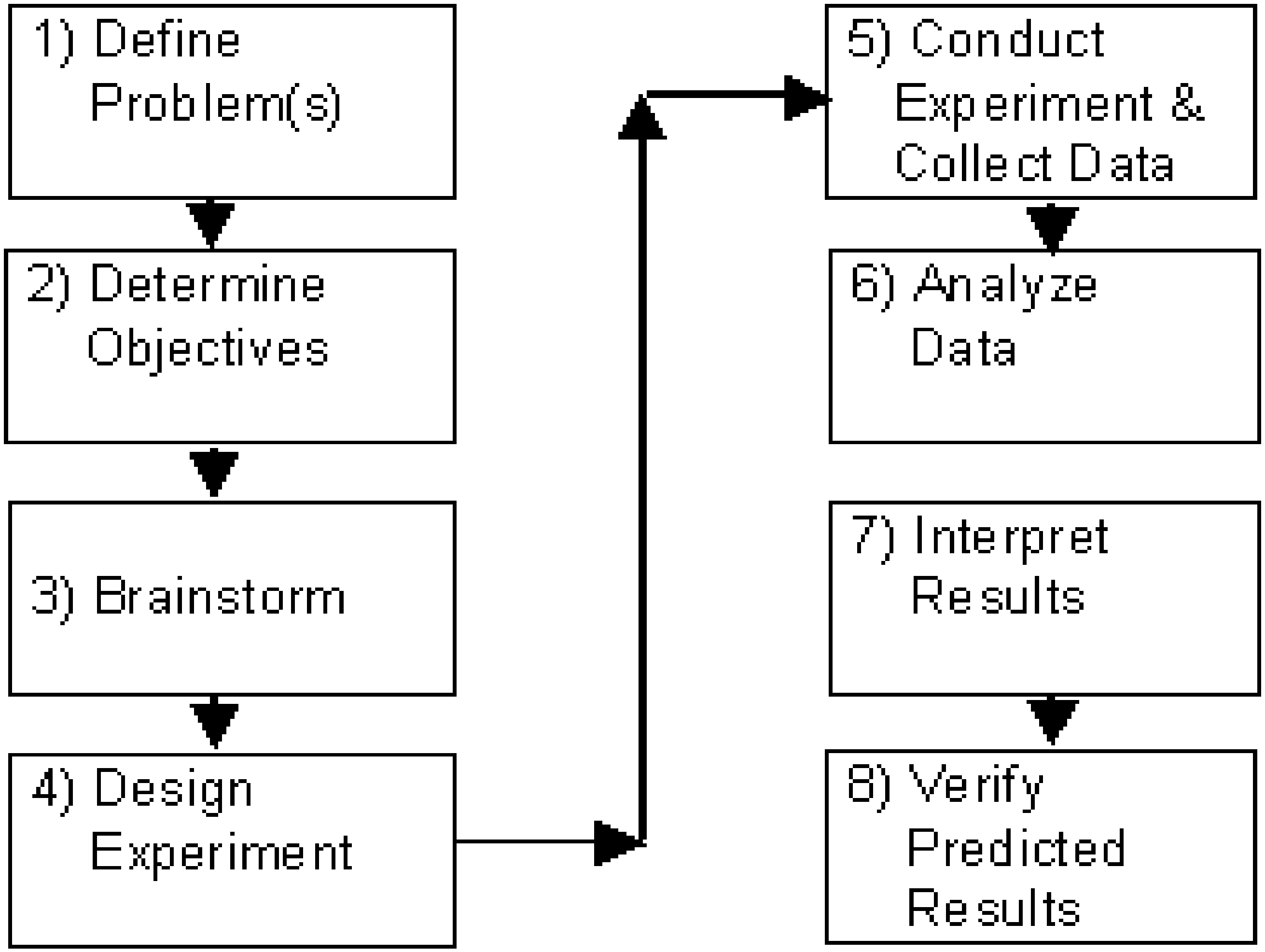
EXPERIMENT DESIGN PROCESS

ADITYA PHARMACY COLLEGE

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

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.

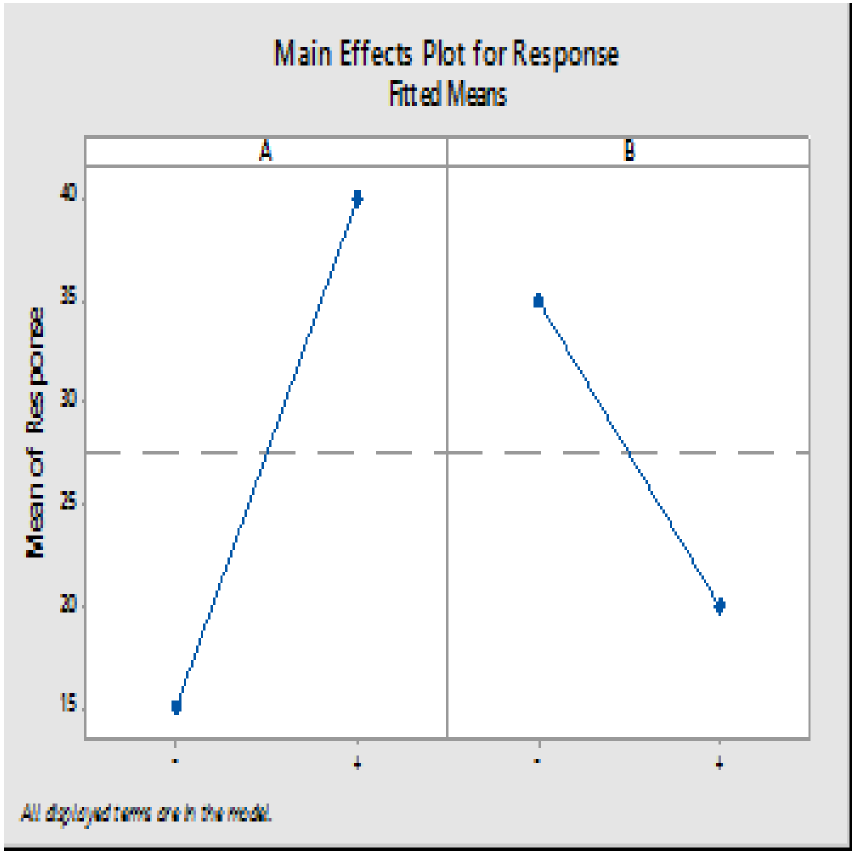
2. FACTORIAL METHOD: The simplest of the two level factorial experiments is the design where two factors (say factor A and factor B) are investigated at two levels. A single replicate of this design will require four runs.

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

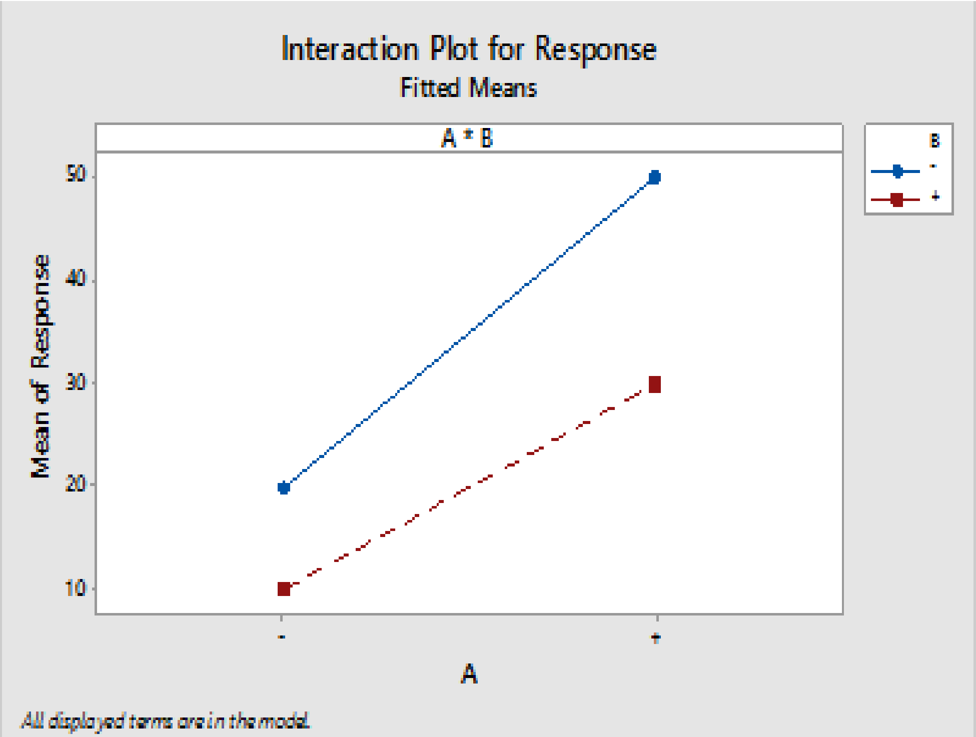


2 FACTORIAL METHOD:

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

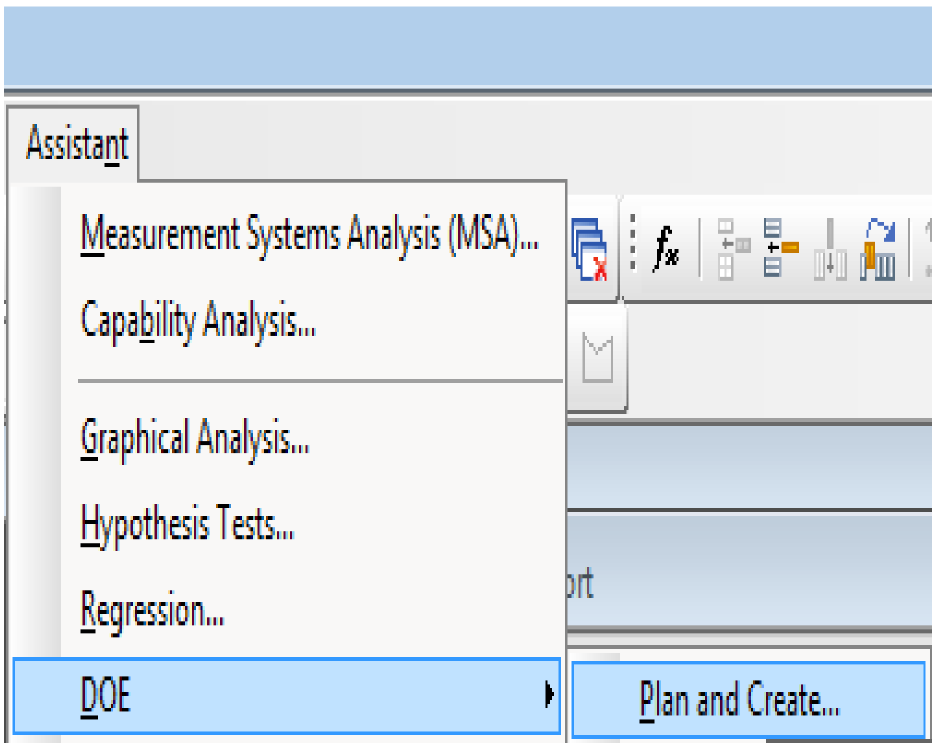
Interaction effect of A*B
= Mean response at+ level – Mean response at -level
= (30+20)/2 – (50+10)/2 = 25 – 30 = -5

Interaction is obtained by multiplying the factors involved

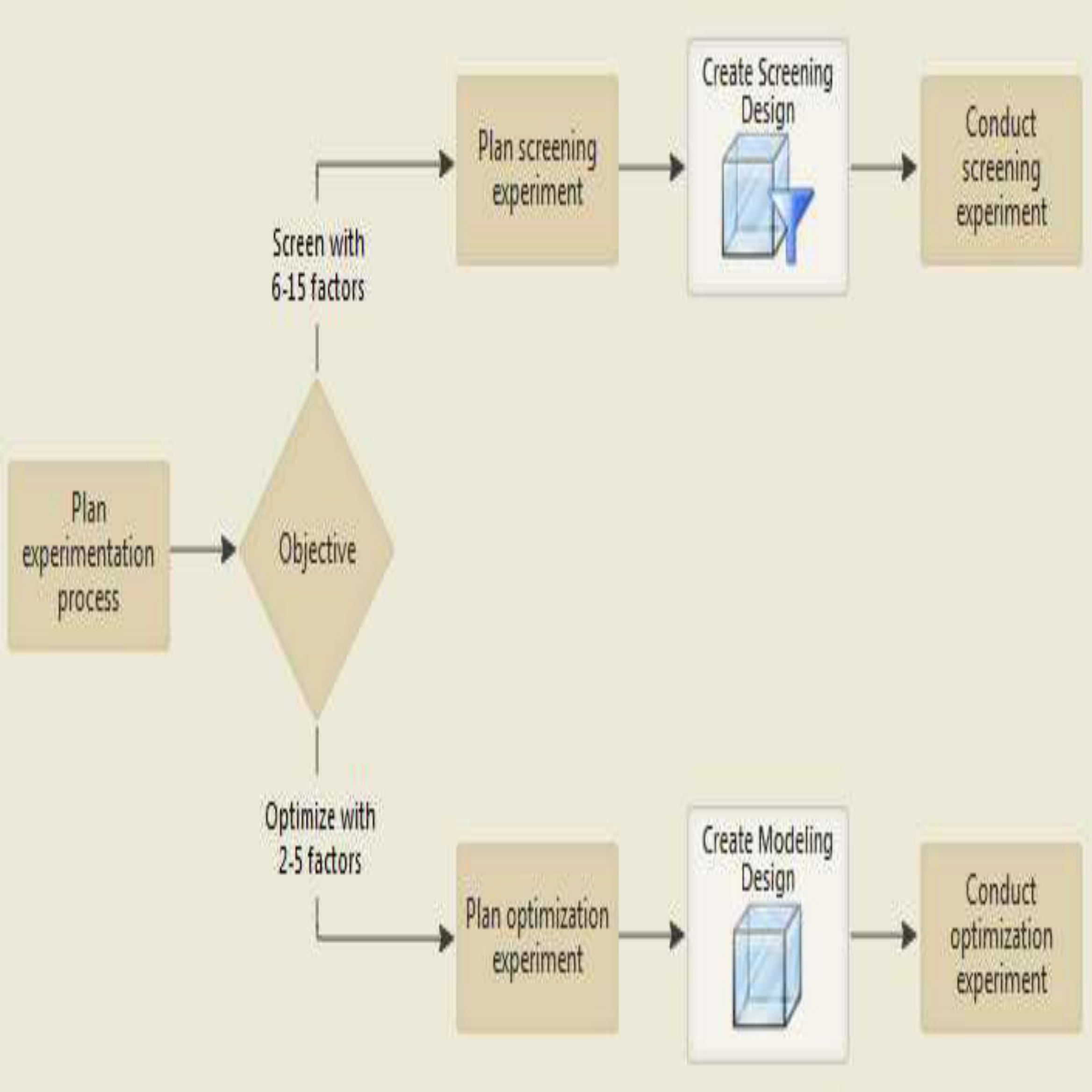


Run #	A	B	Response
1	+	+	33
2	+	-	56
3	-	+	16
4	-	-	26

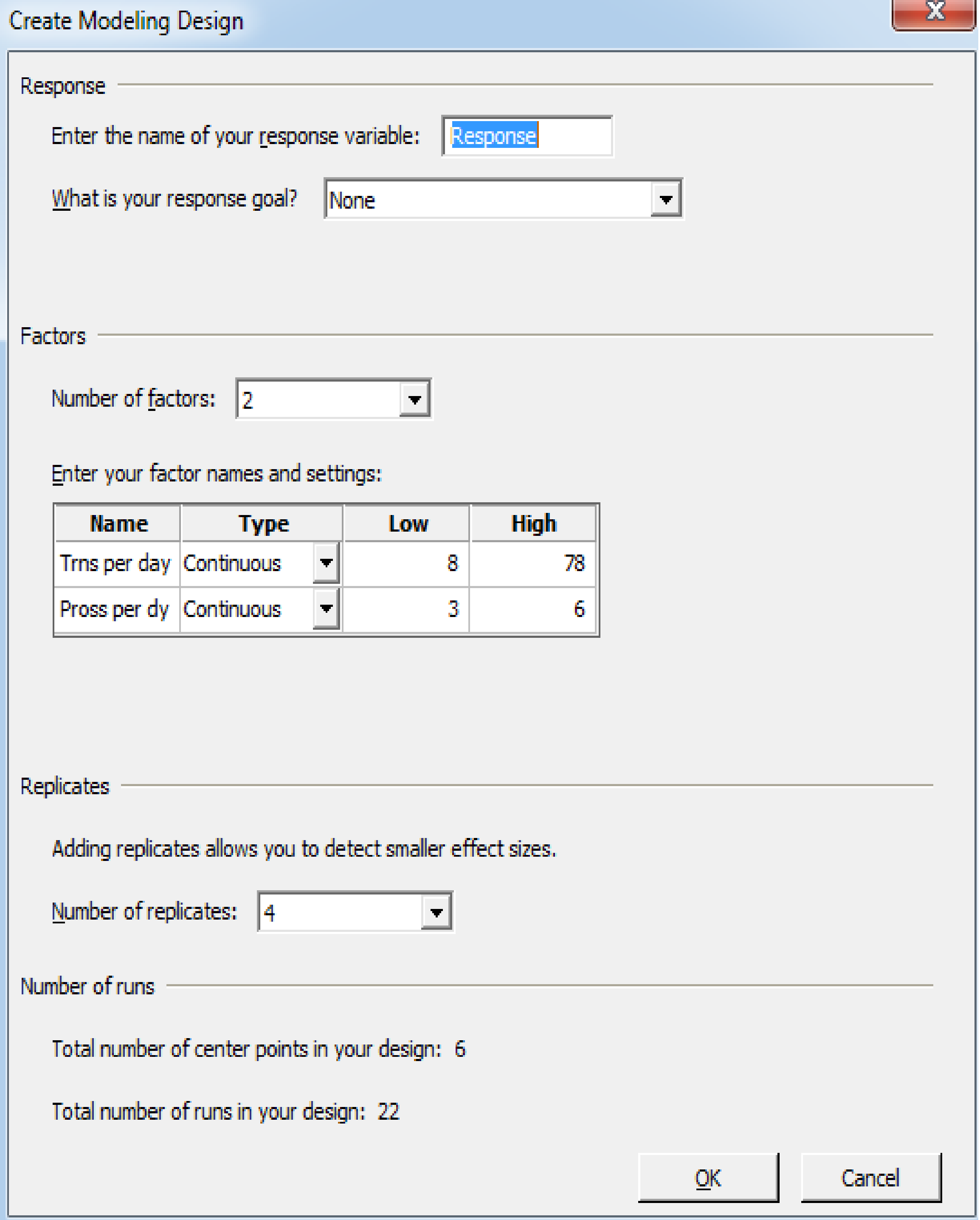
EXAMPLE:



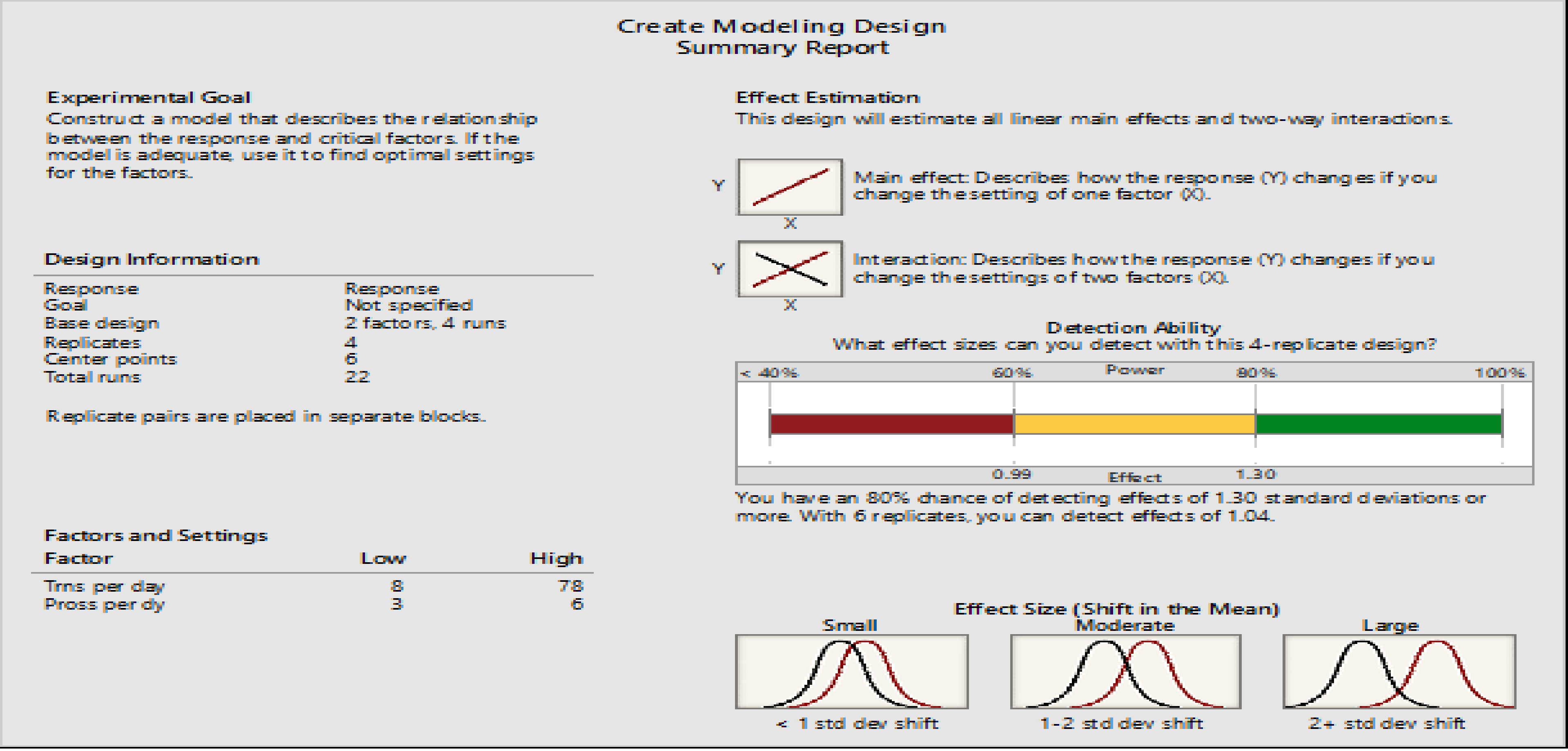
- Go to Standard tool Bar
- Move cursor to **DOE**
- Select **Plan and**
- **Create**



From below popup select ***Create Modeling Design (as*** we are dealing with 2 factors for now)



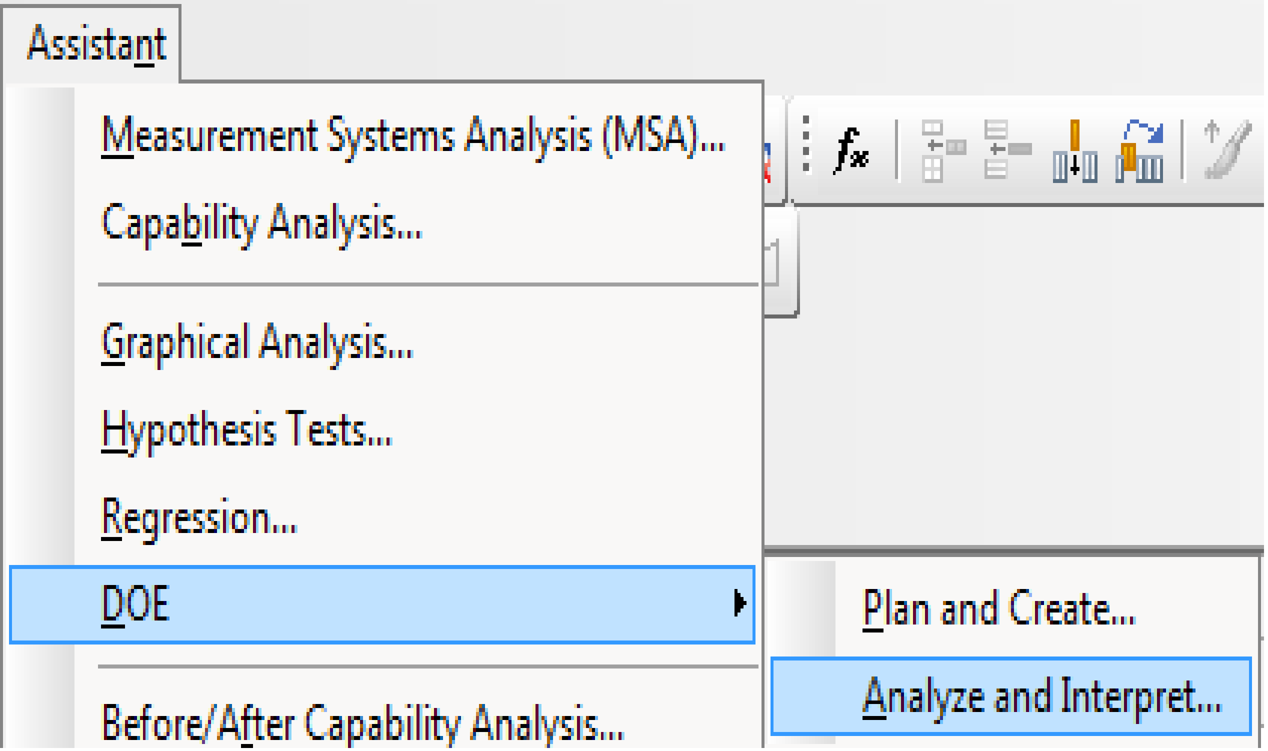
- Enter the Name of the Response Variable (or leave as is as **Response)**
- Select the **Goal**
- Select Factors as **2**
- Enter **Factor Names and Settings**
- Enter the No. of replicates (here it is 4)
- No. of runs auto populate based on factors and replicates



- 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)

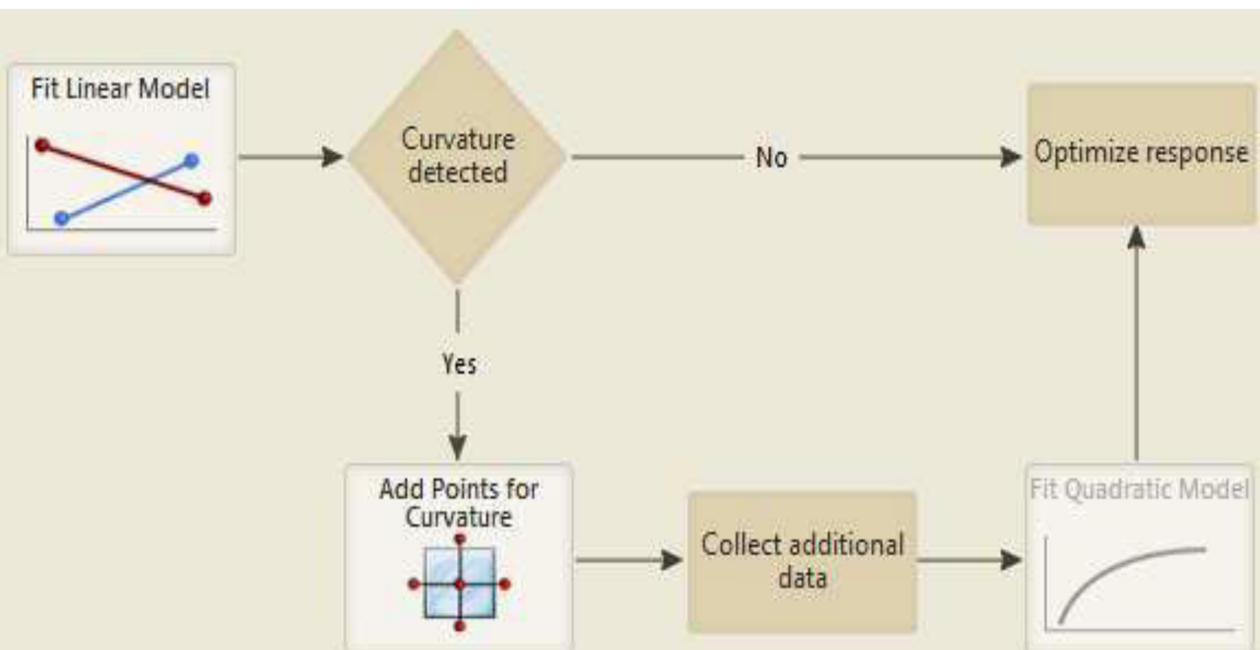


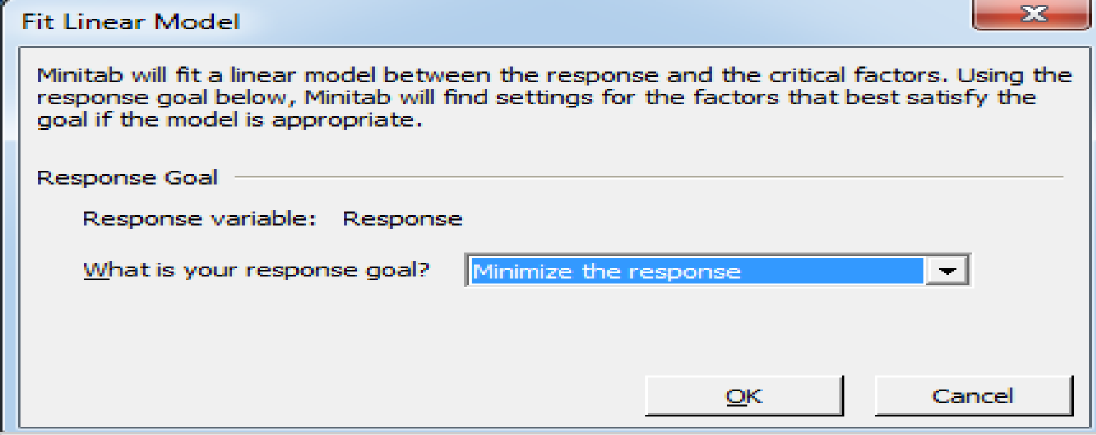
Go to Standard tool Bar

Move cursor to **DOE**

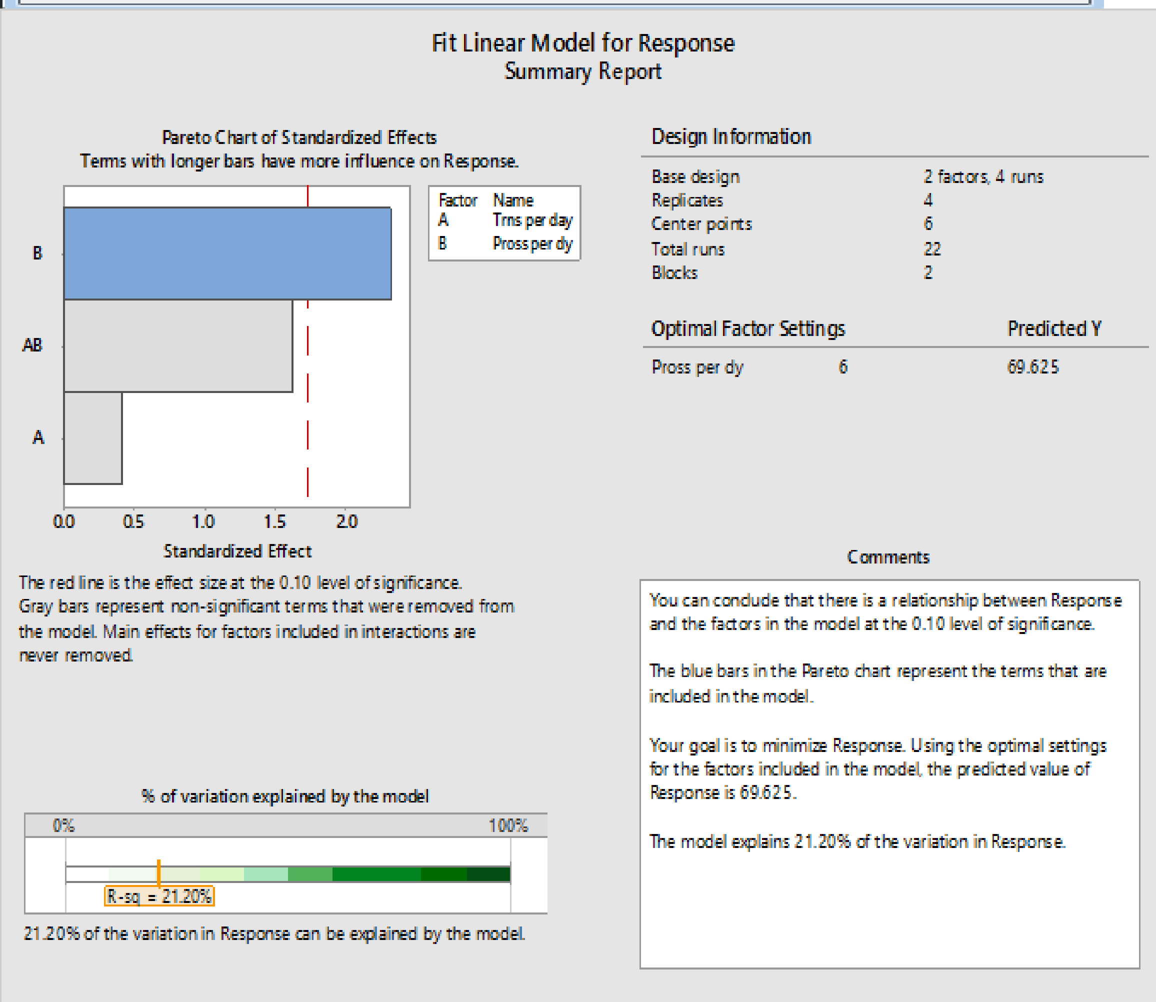
Select **Analyze and Interpret**

From below popup select ***Fit Liner Model***





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



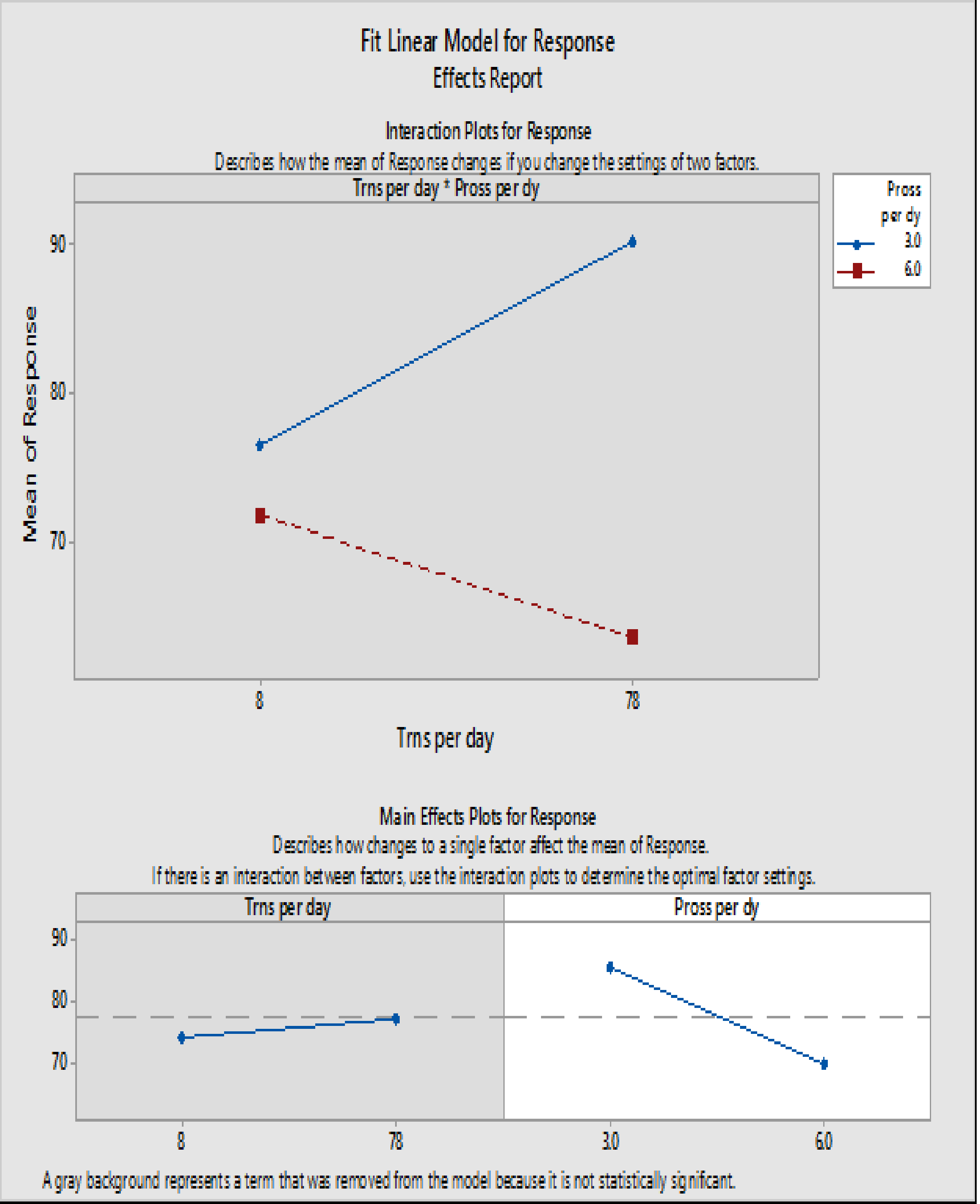
summary Report

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



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.

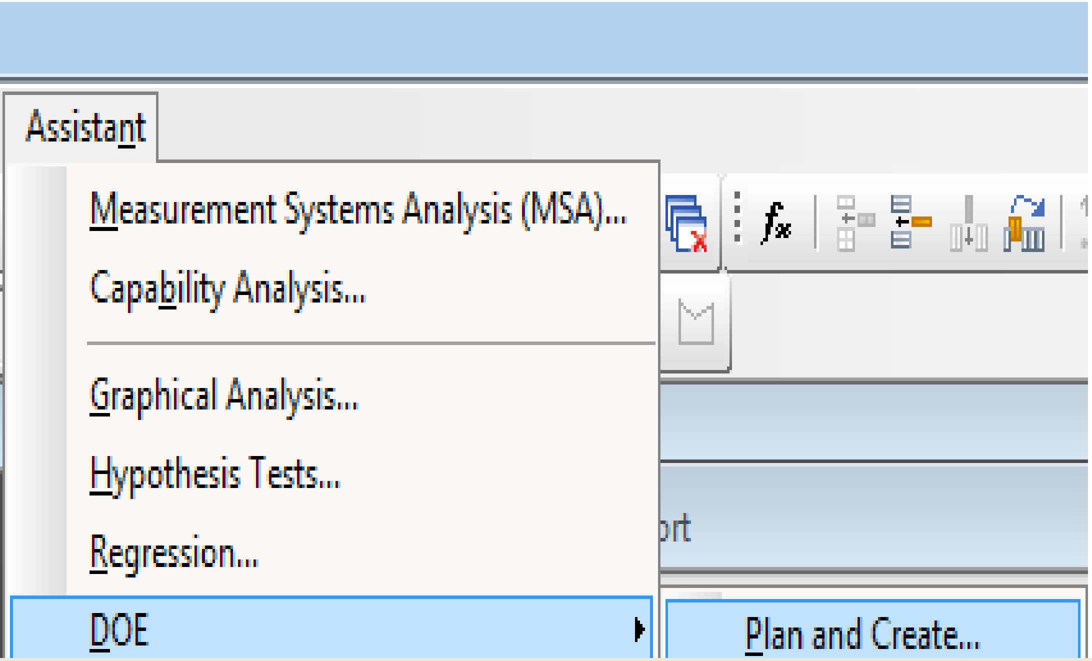
They literally screen the factors, or variables, in the process and determine which are the critical variables that affect the process output.

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.

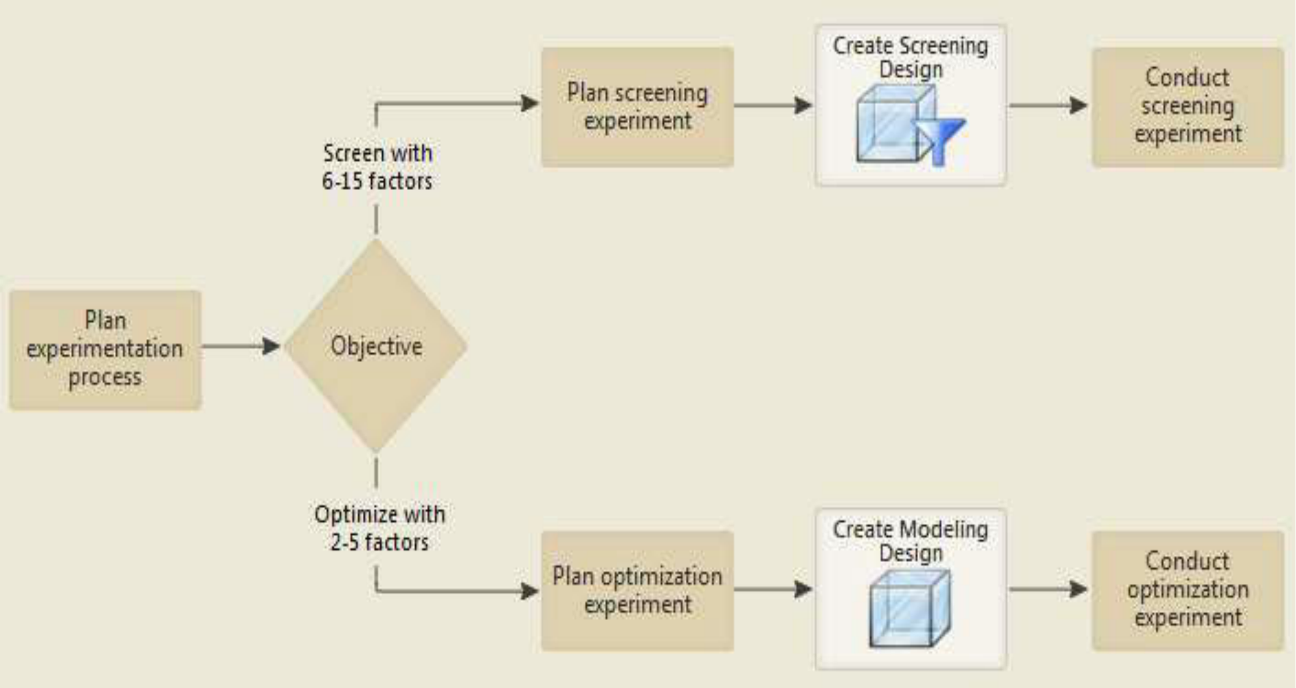
Example:



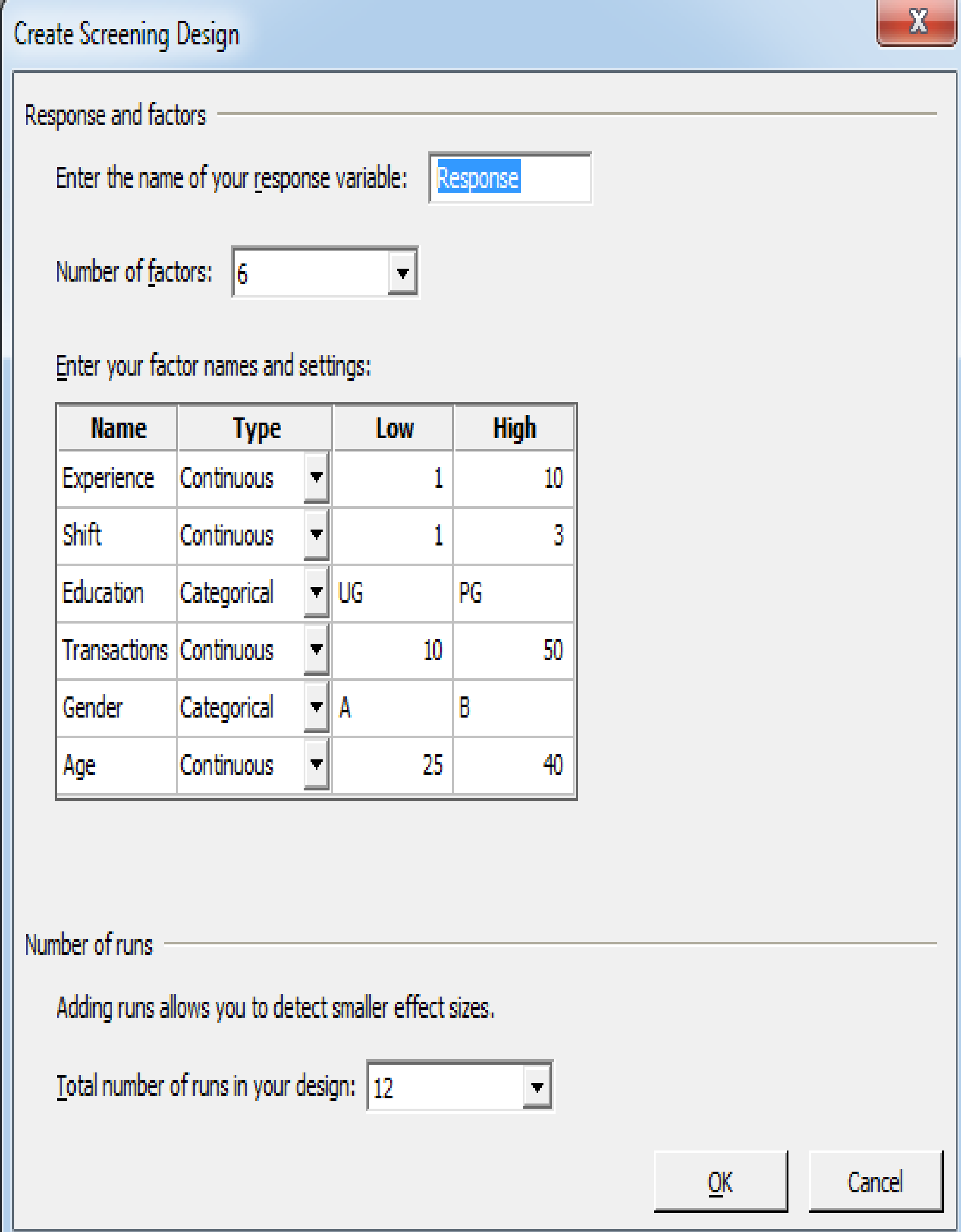
Go to Standard tool Bar

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)



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

Select Factors as **6**

Enter **Factor Names and Settings**

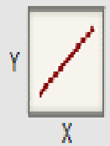
Select the No. of runs

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.

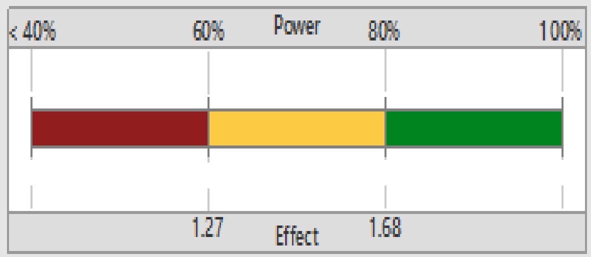


Main effect: Describes how the response (Y) changes if you change the setting of one factor (X).

Design Information

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

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

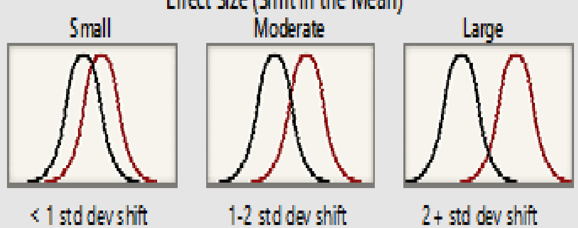


With 12 runs, you have an 80% chance of detecting effects of 1.68 standard deviations or more. With 24 runs, you can detect effects of 1.06.

Factors and Settings

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

Effect Size (Shift in the Mean)

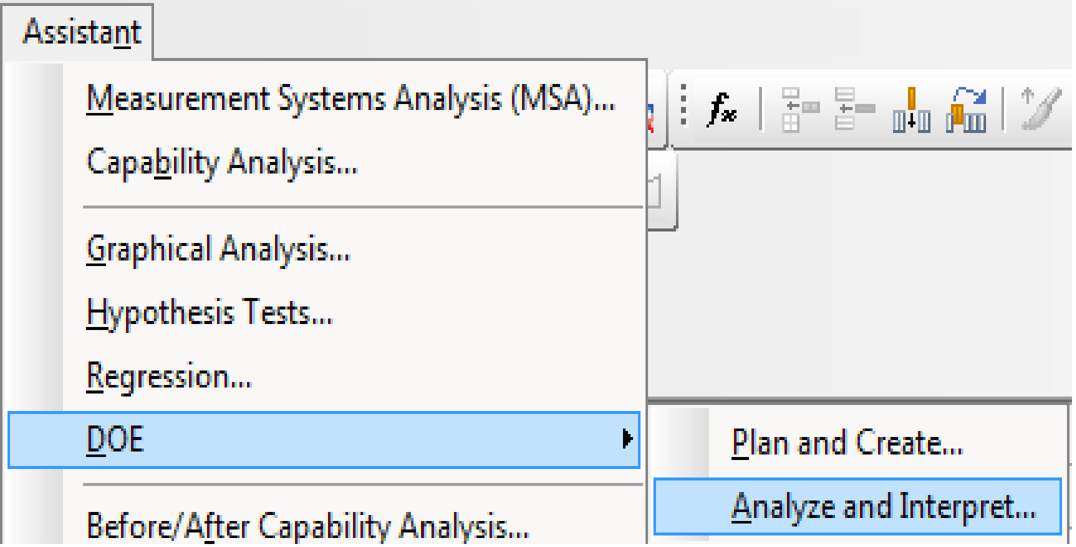


Modeling Design Graph would appear with below details

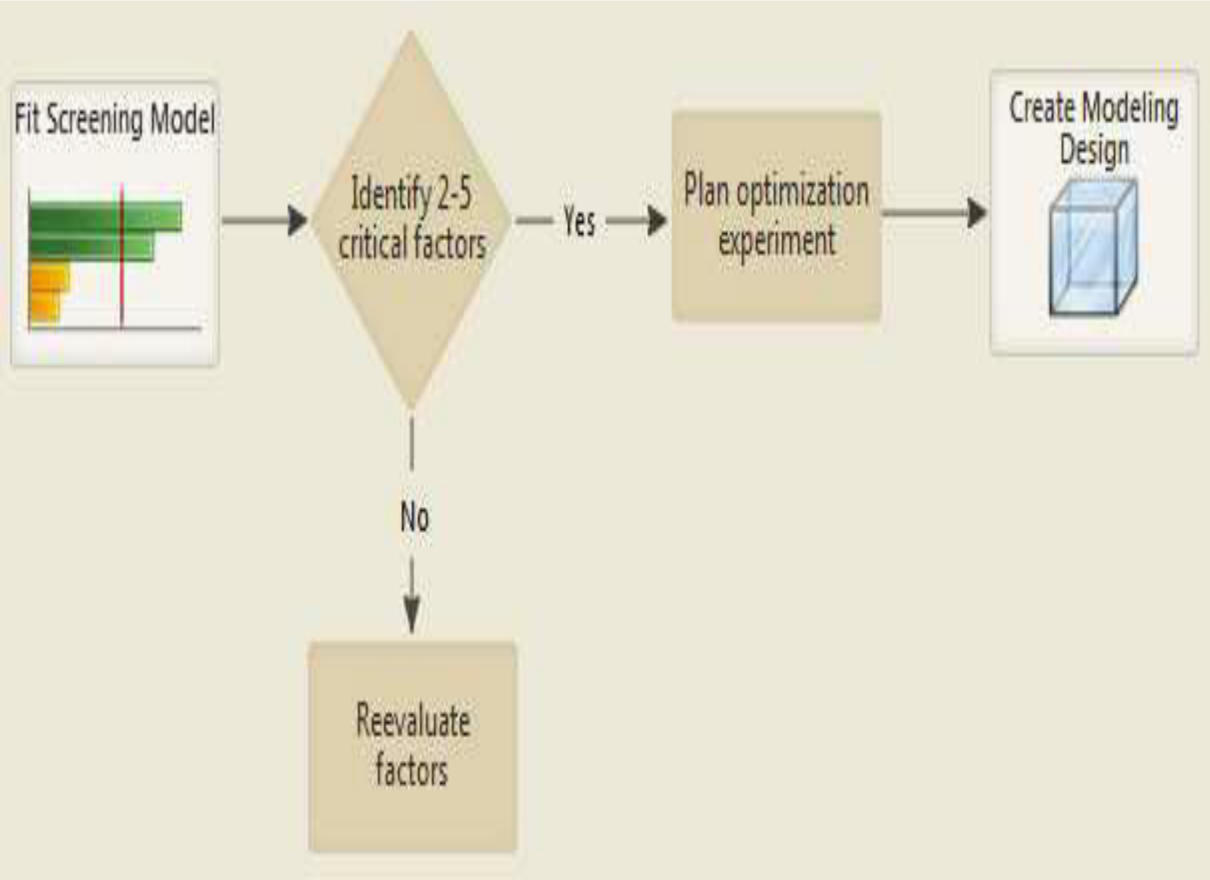
- Experimental Goal
- Design Information
- Factors and Settings
- Effect Estimation
- Detection Ability

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

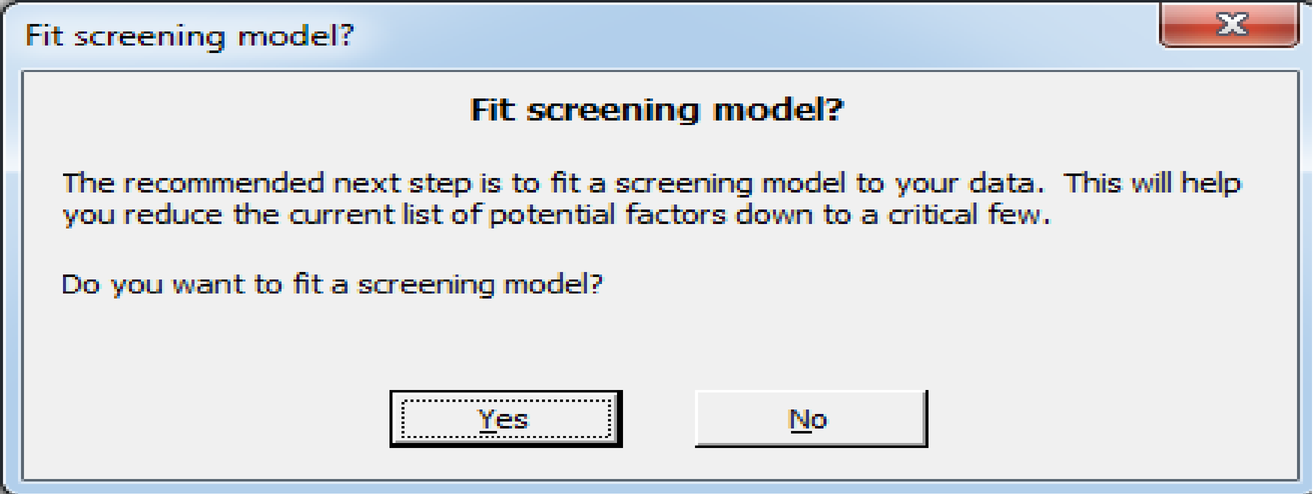
Enter your responses in Response column (C11), Quality scores



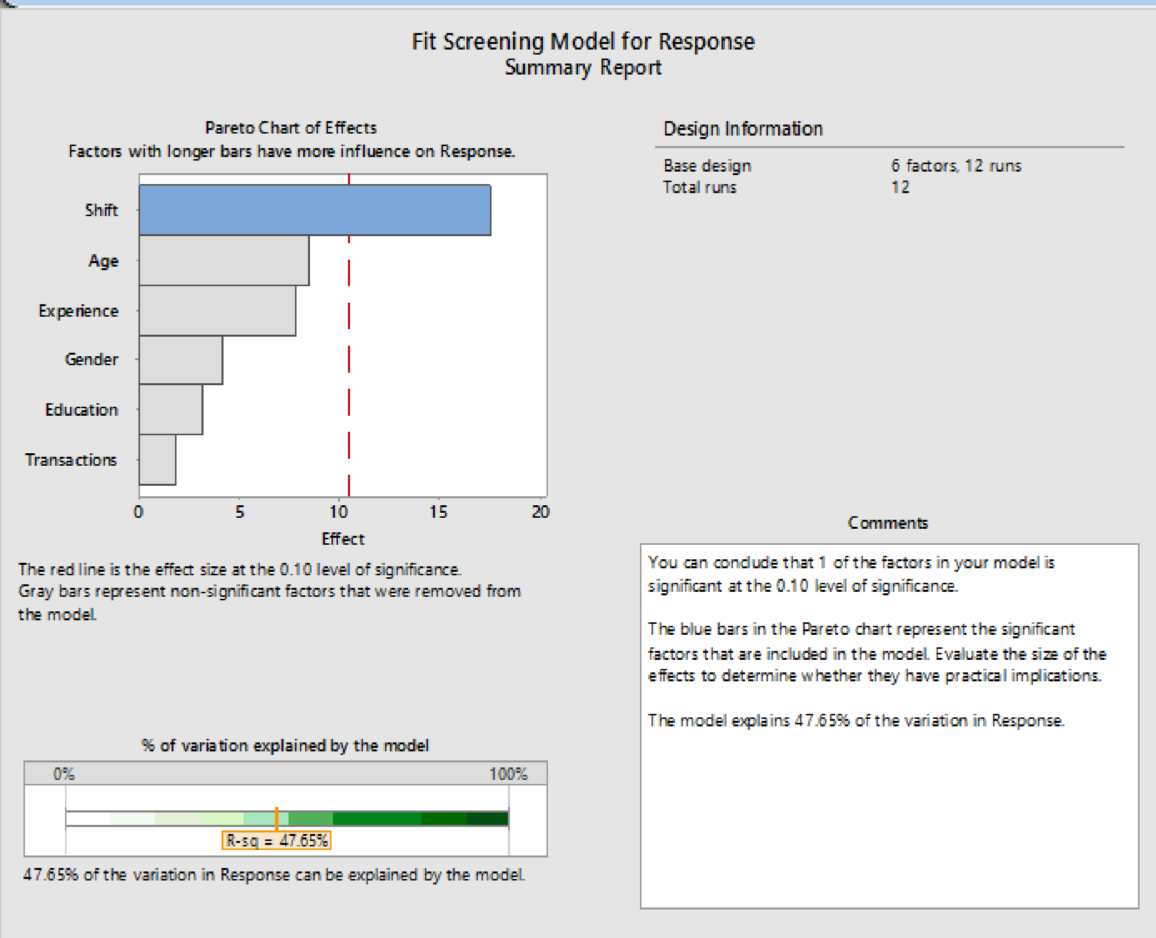
Go to Standard tool Bar
Move cursor to **DOE**
Select **Analyze and Interpret**



From below popup select ***Fit Screening Model***



From below popup select ***Yes***



summary Report

you can identify signifying factors

from Pareto chart

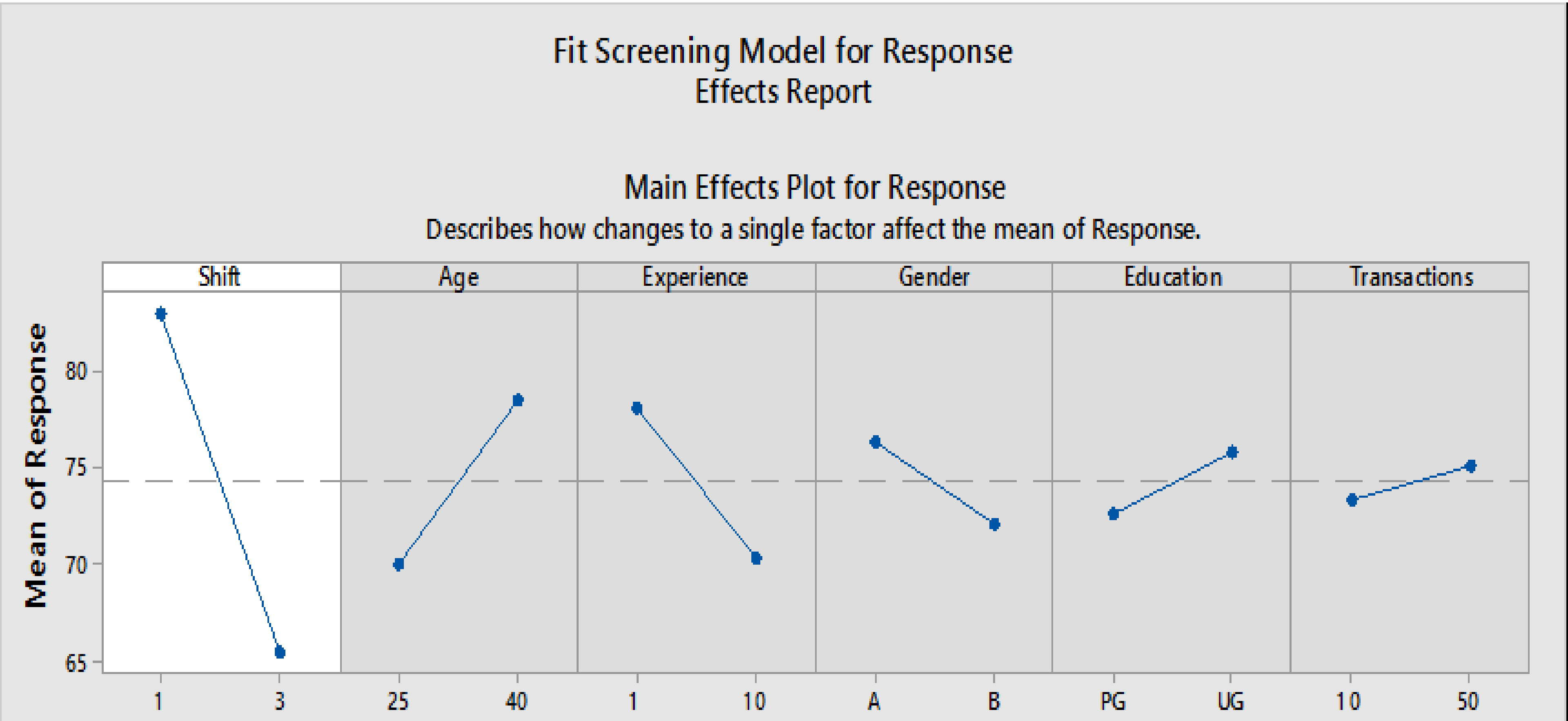
Here it is Shift i.e., shift has more impact on Quality

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