Data Driven Web Experimentation on Design and Personalization

Rasika Irpenwar, Nakul Gupta, Rahul Ignatius and Mathangi Ramachandran
[24]7 Ilabs, Bangalore, India

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Abstract: In today's world for we use online medium for virtually every aspect of our lives. Companies run controlled web experiments to make data driven decisions, to provide an intuitive online experience. We see a big correlation between online customer behaviors and designs and personal treatment, which could be used to create better customer engagement. In this paper we have studied the impact of design elements on *chat invites**, by running experiments on a small population, using machine learning algorithms. Based on this we identify significant elements and build the most opportune personalized messages on invites. Statistical results show that, more visitors on the website accept chat invites which are personalized and optimized for the design.

At [24]7, we have experimented extensively on user inter- face designs and journey based personalization which resulted in positive impact on our annual revenue.

1 INTRODUCTION

At 24/7, we provide *predictive chat** solutions followed by various levels of optimization, which involves a lot of re- search around design and context. Design of Experiments (DOE) is one of the important levers for optimization. DoE's are traditionally used in industrial engineering /mechanical/ in manufacturing units to maximize the outcomes.

We use DoE for online controlled experimentation on chat invites / forms / web page / feedback forms etc. The readings from DoE (significant variables) give the optimized invites. Since chat text came to be one of the significant variables in DoE, we extended the scope of experimentation to context driven text on chat invites.

Defining Design of Experiments: helps in breaking the experiment into components and identifying which of those components would make an impact on the conversions and we can test different Variables/ factors in one experiment. Here we know the factors affecting a process and the output of that process. Unlike traditional A/B test or one at a time test, where we would know the better performing template but we would not know why it is performing better? DoE gives us an edge over other types of experimentation and answers more granular detail of what works.

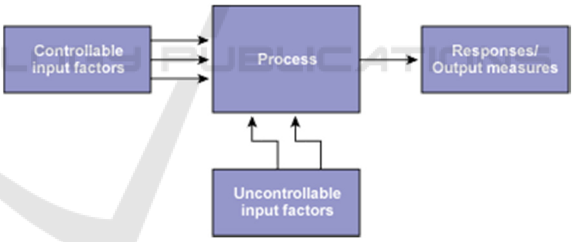

Figure 1.

**image from online article. https://www.isixsigma.com/tools-templates/design-of-experiments-doe/design-experiments-%E2%90%93-primer/*

For ex: One of the retail client, we saw low acceptance of the chat invites. Here our outcome was to improvise the acceptance rate of the invite.

We have taken a Proactive chat invite as an example be- low, proactive chat invite, hereafter referred as chat invite are chat invitations that pop-up on a website asking the user if she/he would like to chat with a customer service representative. This is more powerful than the button chat invites as these are targeted at specific audiences who have high

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propensity to buy or need help in solving their issues. Increasing the *acceptance rate is the outcome here. * **Acceptance rate= (Number of customers who accepted the invites)/ (Number of chat invites shown)**

2 DEFINING THE OBJECTIVE

We need to answer the questions below:
a. Why do we want to run an experiment? What is the outcome we want to measure?
b. What is the effect of experiments on conversion?
c. Is he a potential buyer customer etc.?
d. What can be specifically done to reduce the decline rate of the invite?
Design of Experiments can be used to find answers in situations such as:
e. What are the main contributing factors to enrich the user experience / improving conversions etc.?
f. How well does the system/process perform in the presence of noise?
g. What is the best configuration of factor values to minimize variation in a response?

This can shed light on complex aspects of decision making during the buying cycle of the customer.

3 DETERMINING THE FACTORS AFFECTING THE WHOLE PROCESS

A lot of research on the brand goes into this. The brand connects to its audience through different medium like TV, radio, stores and online market. The behavior on the different medium needs to be studied with the brand guidelines. Factors are determined after quite a lot research on usability perspective, competitor analysis and call to actions.

Factors: Determining X parameters having Y levels. Parameters are variables within the process that affects the performance measure such as sound, color etc. that can be easily controlled. The number of levels to the parameters should be varied and must be specified. Increasing the number of levels to vary a parameter increases the number of experiments to be conducted.

As we use Taguchi's method for designing the experiment. Hence we should ensure that the factors are independent of each other. Hence we need not measure the interaction effect. The factors should be independent of each other, if we are not measuring the interactions.
For example: It can be anything from imagery, size, place, font, color, shape. In experiment we used these factors with 2 levels each.
Factors being: Sound (yes or no), text color (blue vs red), content on the invite, transition, text cases etc.
Here **levels** being: Yes vs no, for Sound.

Design the Experiment: Once we have the factors and levels to it, we design our experiments. We design a matrix in such a way that all the factors and its levels are being experimented. There are many ways in which a DOE can be applied, but here we are sticking to Taguchi’s method to run experiments. This approach uses the fundamental idea of DOE, but simplifies and standardizes the factorial and fractional factorial designs.

Fractional Factorial: is used to reduce the number of experiments. A fractional factorial design of experiment (DOE) includes selected combinations off actors and levels; it is a representative subset of a full factorial design. A fractional factorial DOE is used when the number of potential parameters is relatively large because they reduce the total number of runs required. In general, higher-order interactions are confounded with main effects or lower-order interactions. Since higher order interactions are rare, usually you can assume that their effects are minimal and that the observed effects are caused by the main effect or lower-level interaction.
Taguchi’s way uses orthogonal arrays, as this makes it possible to carry out fewer fractional factorial experiments than full factorial experiments.

Orthogonal Arrays: are used to determine the matrix. Orthogonal arrays are a set of tables of numbers, each of which can be used to lay out experiments for a number of experimental situations.

Types of Fractional Factorial Design: Orthogonal (balanced) arrays, Latin Squares etc.
Example: Factors = 5 and levels=2, Full Factorial Experiment = $2^5 = 32$.
Full factorial leads to 32 experiments to run. Hence using fractional factorial we can run 8 experiments.

As our outcome is acceptance rate, we define it as

Acceptance Rate = *fn* (Text Color, Text Cases, Transition, Sound (notification), Border with Shadow)

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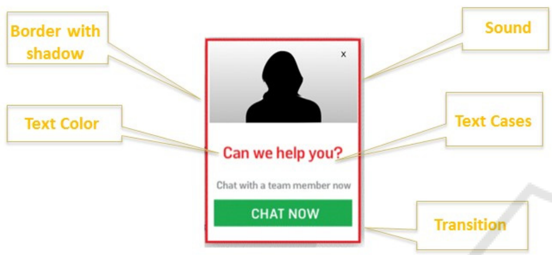

Figure 2.

4 TARGET AUDIENCE

The target audience is the ones who will actually see these experiments. Knowing the target audience is one more crucial step. Which means who do you want to target, what % of your total population you want to experiment with and when?

5 VOLUME ESTIMATES

Volume estimates can be determined as per the number of experiments and duration of the experiment. The traffic per page can be considered and desired % can be given for each experiment. Each experiment, falls into particular target population (TP) bucket. We would a control group, against which we would measure our test group performance.
Example: Here each experiment gets an exposure of 10% of total traffic/population of the website. Visitors are divided into 8 + 1 = 9 random groups i.e. 8 Test groups and one control group. 8 test groups were show one of the 8 invites and the control group was shown the existing invite.

6 EXPERIMENTATION DURATION

During the course of the experiment, the data starts to flow into our servers for analysis. We collect data such as number of invites shown, number of invites accepted etc. We ran this experiment for 2-3 weeks. The duration of the experiment is based on the number of experiments, traffic/volume, seasonality etc.

7 ANALYZING DATA / RESULTS

The initial step is finding the significant variables and finding the interaction between variables if any. After this we interpret ANOVA results. ANOVA (Analysis of Variance) is a statistical technique that identifies factors significantly affecting the experimental results.

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ANOVA consists of summing squares for distributions of all characteristic values (experimental data), unbiased variance, decomposing this total sum into the sums of squares for all factors used in the experiment, calculating unbiased variances through the sums of squares for all factors over their DOF and searching which factors significantly affect experimental results by analyzing the error variance.
For example: Of the original 5 variables which we experimented, only two are statistically significant variables.

- Sound: Invite with Sound (yes), was one of the most significant variables
- Transition: Invite with middle right transition was the second most significant variable.

We analyzed the data using Generalized Linear Model (GLM) and ANOVA.

GLM Model to estimate the effect of factors on Acceptance Rate
$Y_i = \beta_0 + \beta_1 x_i + e_i$

'k' factor ANOVA Test of significance of factors

Table 1.

Factor	Estimate	Sum Sq	DF	Mean Sq	F-Ratio	p-value
Text_color (Black)	7.12E-05	2E-07	1	2.20E-07	0.035	0.852
Text_Cases (UC)	-2.93E-04	3.8E-06	1	3.77E-06	0.587	0.445
Transition (MCERMS)	4.68E-04	9.6E-06	1	9.64E-06	1.502	0.222
Sound(Yes)	2.39E-03	0.000251	1	2.51E-04	39.148	3.08E-09
Border (RDS)	3.11E-05	0	1	4.00E-08	0.007	0.935
Residuals		0.001091	170	6.42E-06		

Acceptance: 14.3\% incremental chat assisted sales over the control group. The best combination had the sound and transition. Wherein text color,text cases, border were not the significant variables; they had no impact on the acceptance rate.

Post Experiment Results: The winning invite was ramped up to the whole population. And further used for contextual invites.

Impact of DOE: The winning invite is then used as base invite for any initiatives.
After running the experimentation with different design variables on the invite and arriving on the optimized design, the next phase involves experimentation on the invite text. In the following section of the paper we will discuss the experimentation on invite text based on customer web journey, personalization etc. to bring in value to business with more acceptance rates on chat invites

8 OPTIMIZING CONTENT ON CHAT INVITES BASED ON USERS JOURNEY

Personalization of experience for end users is of utmost importance for any industry in the online space. Companies typically use significant amount of data from the below streams to identify segments and devise their targeting strategy.

- Demographics Age, Gender, Employment status, etc.
- Psychographic Lifestyle, Interests, Opinion, etc.
- Behavioral Browser History, Purchase History, Internet Behavior, etc.

*In the following sections of the paper personalized invites should be referred as chat invites shown to the customers on a website based on the intent of the customer.
Personalized invites introduces a sense of relevance in otherwise generic chat invites and results in more people accepting the chat invites as compared to the number of people who would have accepted the chat invites in generic scenario (i.e. without personalization). Personalized chat invites generally works on top of already existing predictive data models, which identifies what customers should be shown chat invites.
For example: Following are some of the contexts which were passed in the proactive invites on the website of one of our retail clients. Following are some of the contexts which were passed in the proactive invites-
”**Welcome Back**” on the pro-active chat invite to a repeat visitor
”**Looking for Furniture**?” or ”**Buying a washing machine**?”
Above exercise was intended to accomplish higher chat acceptance rates by showing personalized invites based on customers intents.

9 UNDERSTANDING CUSTOMER INTENTS, QUERIES AND TARGETED SEGMENT

We identified top intents by analyzing one month of chat transcript data. High volume intents revolved around seeking help on product (e.g. product info, Comparison, offers, features etc.) and cart related activities.
To roll up intents under meaningful boundaries we took following into consideration

- Understanding and analyzing the granularity of in- tents.
- Finalizing the granularity of personalized invites de- pending on the variations in resolution types, query types etc.
- Estimating the volumes of the finalized intents

We dived deep into these intents using a supervised learning approach and identified top products which drive high chat volumes.
We started with identifying the intents based on chat acceptance on various pages, manually tagged transcripts to intents and then ran a supervised text classification to estimate the volumes. **Below are some statistics used in above analysis :**

- **Chat volume:** 25,000 to 30,000 sales chat transcripts.

- **Chats from Product Pages:**~90% of sales chats
- **Chats from product pages:** ~ 86% (In which customer come to chat about product)

Top Product Categories:

**We choose "Home and Garden", "Technology", "Sports and Leisure" and "Toys" categories for personalized chat invites since most of the chat volumes fell under these product Categories.*
**Since "Home and Garden" Category was one of the biggest chat drivers we broke it down further into product sub product categories.*

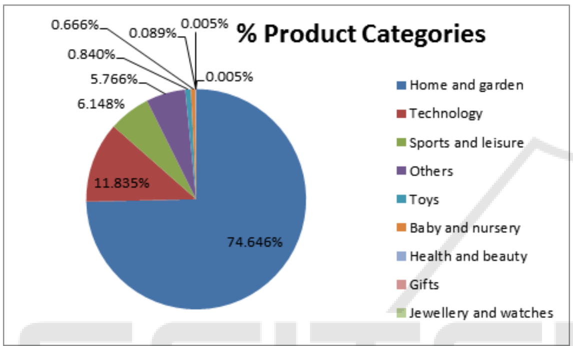


Figure 3.

Following are the intent categories for which personalized invites were created:

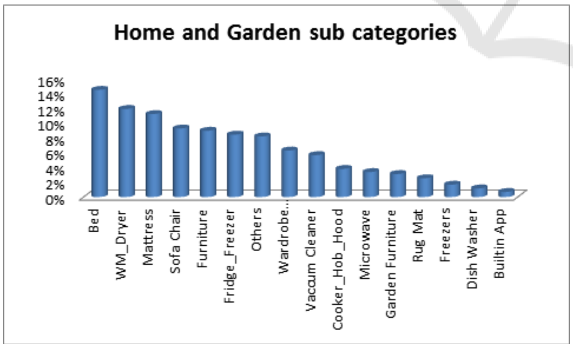


Figure 4.

Below are few examples

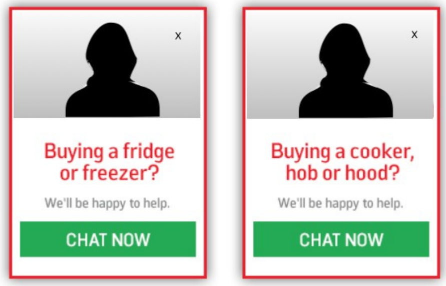


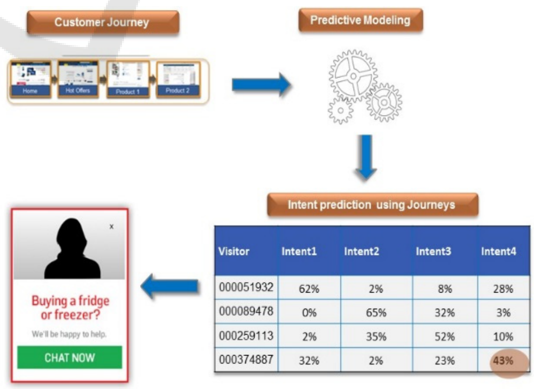
Figure 5.

10 INTENT PREDICTION AND INTERVENTION

We attributed concatenated customer web journeys and other customer attributes and used supervised text classification algorithms to predict customer intents real-time.

Examples:

1. A visitor whose last two pages were refrigerator pages and has spent at least 30 seconds on the current page would be shown a personalized refrigerator invite.
2. A visitor, who spends at least 40 seconds on a hob page, will be shown a personalized hob invite.



Visitor	Intent1	Intent2	Intent3	Intent4
000051932	62%	2%	8%	28%
000089478	0%	65%	32%	3%
000259113	2%	35%	52%	10%
000374887	32%	2%	23%	43%

Figure 6.

11 EXPERIMENTATION

Based on randomization algorithms visitors were made to fall under test and control groups.

1. **Test Group:** Where a set of personalized invites were thrown based on customers journey. If the customer is not eligible for a personalized invite then they are shown generic "Can we help you?" invite.

2. **Control Group:** Generic "Can we help you?" message was shown in all the cases irrespective of customer's web journey.

Some Statistics:
Total Number of chats (Sales) per day: ~1100
Chats on Product Pages: ~90% of 1100 = 990
Test Group = 10%
Chats per day for Experimentation = 10% of 990 = 100
Personalized chats in test group: ~80%
** To establish which of the group has better acceptance rate among test and control with 95% confidence we need approximately 1300 data points, which in this case is represented by number of chats*
No. of days of Experimentation = 1300/80:~2.5 weeks

12 DATA ANALYSIS AND RESULTS

We observed the acceptances rate for both the groups for a period of 4 weeks and found that the test group with personalized invites had an overall impact of ~9% increase over control group.

Week1				Week2		
Test Group	Control Group	% Difference		Test Group	Control Group	% Difference
0.62%	0.57%	9.05%		0.59%	0.55%	6.96%
Week3				**Week4**		
Test Group	Control Group	% Difference		Test Group	Control Group	% Difference
0.59%	**0.55%**	**8.28%**		**0.68%**	**0.61%**	**10.72%**

Figure 7.

Significance Testing: We performed significance testing on Acceptance rates on a daily basis and concluded that the Test Group Acceptance rates are greater than Control Group acceptance rates at $p < 0.001$, using Wilcoxon Test.

13 CONCLUSION AND FUTURE OPTIMIZATION

As the above example shows we can measure the impact of factors being changed.

- DOE is economical technique as it takes less runs of experimentation. Results can be obtained based on a performing small number of experiments.
- These well-designed experiments will yield statistically sound interpretations. For further work we are Optimizing content based on user journey and personalization of the invites. Also, we are trying new approaches using other statistical methods, introducing new tools to fasten the process. Also implementing new innovative ideas and techniques to make the system for robust and getting good conversions.
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14 COMMON CHALLENGES

- Identifying the variables. The system should be robust and strong to take up these changes.
- Read out time can vary and also interfere with seasonality or other changes.
- Overall coherence with the site in defining the factors.
- Nearly similar intents like setting up vs setting password for an email client
- Performance challenges after going live, due to change in interface.

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