Study on Web Analytics in B to B Manufacturer Industry

March ２０１６

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Summary

Business-to-Business (B to B) manufacturer web sites have changed in role and responsibility since use of the Internet has become widespread even among engineers. Visitors to B to B web sites have a variety of goals and web site requirement has different characteristics from B to C like more over-session accesses. In my study, I have two following premises for values of web analytics for manufacturer companies. (1) Improve and optimize the site in user behavior and (2) Use in marketing activities like as knowing user requirements. Considering the B to B dedicated characteristics, I tried analyzing user typical behavior and created methodology for B to B web site web analytics.

I have developed web analytic framework including path analysis, participation to conversion, user registration analysis for carrying out site optimization for usability and making use of data for marketing. I have confirmed that especially user registration is important. I tried to use page dwell time as additional Key Performance Indicator (KPI) metric as well as typical KPI metrics. In addition, confirmed that page dwell time is effective to measure user stickiness to web sites. I created analytic segmentation model and examined web access effectiveness using some segments like information, user environment, user behavior, and business. I have pointed a case from a manufacturer and investigated initial situation where the firm had non-negligible exit rate due to the demanding on-line user registration form. I have tracked the manufacturer's on-line registration forms and their resulting figures such as number of visitors and relevant conversion rates. Then, I have analyzed the context and content of the manufacturer's web registration forms using those web registration form related metrics as a key. From the context perspectives, I demonstrated that number of registration steps, number of input fields and number of required fields, could be a factor of the conversion differences. Furthermore, I found type of information being asked, embedded external links and registration form usability are critical factors from content viewpoint. Since there was little study for B to B web analytic for it, basic methodology is provided with actual data in this study.

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1. Introduction

Business-to-Business (B to B) manufacturer web sites have changed in role and responsibility since use of the Internet has become widespread even among engineers. The purpose of visiting a web site has changed from searching for technical documents into searching for solutions or products without any face-to-face contact. In B to B manufacturer industry, traditionally sales related activity or even marketing related activity was tied to face-to-face salespersons' activity. In this period, the web site's role was for searching and for providing technical documents or technical software resources.

With the growth of e-commerce, users are getting hesitant to meet salespeople and at the same time the manufacturer wants to track user behavior on the web and utilize analytic data for marketing and improving sales revenue. The web site is becoming more important than before even from a business point of view even though it was used only for information delivery in the past. In web analytic area, we cannot find any clear B to B dedicated web analytics study.

i. I have two following premises for values of web analytics for B to B manufacturer companies. Improve and optimize the site in user behavior
ii. Use in marketing activities like as knowing user requirements.

Compared to B to C web analytics, B to B web analytics have different characteristics. Considering the B to B dedicated characteristics, I tried analyzing user typical behavior and create methodology for B to B web site web analytics.

With those premises, B to B web analytics framework and Key Performance Indicator (KPI) sets are discussed in this study. The framework includes required analytic items and steps. Also defined basic KPIs and try mixing an additional indicator (Page dwell time) with them for better analytic approach. In addition, I studied the effectiveness of user behavior by segmentation and to define what is suitable for segmentation in B to B manufacturer site. In fact, I tried some case studies and tried to confirm analytic methodology by segmentation.

In another aspect, web registration form on B to B site often works as a gate for privileged on-line and off-line services. In fact, we see that B to B form asks visitors' information for granting access to: whitepaper and technical documentation downloads, customer support such as inquiry and on-line chat, as well as off-line tradeshows and business seminars. Those visitors who have registered in web form are sometimes considered more valuable to manufacturing firm than non-registered visitors because they had taken extra time to fill in registration form and subscribed to the firm's service as well as the firm could initiate marketing action such as sending promotional e-mail based on the registered information. Then, noting the importance of the form, manufacturing firm has been trying to improve usability of the web registration form such that it could increase number of user registration through the form, in other words increase in the form conversion rates. Conversion means to transform "visitor" to "purpose achieved user. I try to analyze web registration data and conversion rates with different versions of web registration form. I try to illustrate and explain two types of manufacturer web registration forms created as a result of improvement. In addition, I analyze exit rate of the web registration forms in detail.

I want to note business background more. The manufacturer business has traditionally focused on large companies as customers. However, the market of large customers has become saturated (especially in Japan), and support for small and medium-sized companies, including the long tail market, must be considered for further business expansion.

However, the strategy of assigning sales staff and performing targeted marketing, which worked for large companies, cannot realistically be used for small and medium-sized companies due to support costs. Therefore, it is critical that in addition to using a website as a medium for providing information to small and medium-sized companies, it should also be used for marketing activities such as collecting user information and getting a handle on the needs of the market.

In addition, web site is getting more self-service way than before. It used to be just user helping tools because most of business are with face-to-face type in b to B but currently more web self-service driven site is important especially for middle and small size customers. Furthermore, the volume of product information is increasing depending on the increasing functionality of products. Moreover, due to increasing numbers of customized products, the number of webpages and database records is ever increasing. Therefore, access analytics need to be used to optimize user paths through a website and so on. Moreover, there is a need to use analytics data for business (especially marketing and sales activities).

Statistical access data set for the global electronic industry company web site from April 2010 to March 2015 is used in this study. We used analytical data consisting of about 20,000 HTML pages, 7000 PDF files, and a 40,000 record product database (for displaying product specifications as parameters). All data in each figure or table without any notation is averaged 6-month data for the manufacturer Japanese site.

2. B to B Web Analytics Issues

2.1. Overview of Web Analytics

Web analytics techniques come in the following types.

i. Server log type
ii. Packet capture type (Sniffing Packet type)
iii. Web beacon type

Server log type was seen in initial internet period because most of the web server application has analytic functions by nature. However when the web site has several distributed servers, it is hard to tack total access counts and user behaviors with several server locations. Packet capture type is good even for distributed server configuration. Most of the packet capture type solutions can sniffer network packets and track access logs. However recently most of the global web service providers or global company web sites use CDN (Content Delivery Network) which allows them to have cache of pages in many locations in many countries. Biggest CDN Company - Akamai Technologies have about 200 k-cached servers and in other words, the same page can be distributed to 200 K cached servers. Therefore, this type of analytic solution cannot track user access easily when user accesses cached sites. Web beacon type is the most used type now for capturing the user path while considering cache. We used this technology through all studies. To compare with other methodology the user behavior can be tracked more precisely especially distributed server configuration.

The basic process of web beacon is the following. As condition of web beacon activation, targeted pages need to embed tracking JavaScript or need to have links to tacking JavaScript.

i. Web client (In most cases it is a browser) requests web server to get page data.
ii. Once web server gets request from web clients, it sends page data to web clients.
iii. When page is displayed in web clients, embedded or linked JavaScript operate and send access related information to analytic servers.
iv. Analytic server typically has data displaying or reporting function and then we can user access data.

Figure 1 shows web beacon basic image.

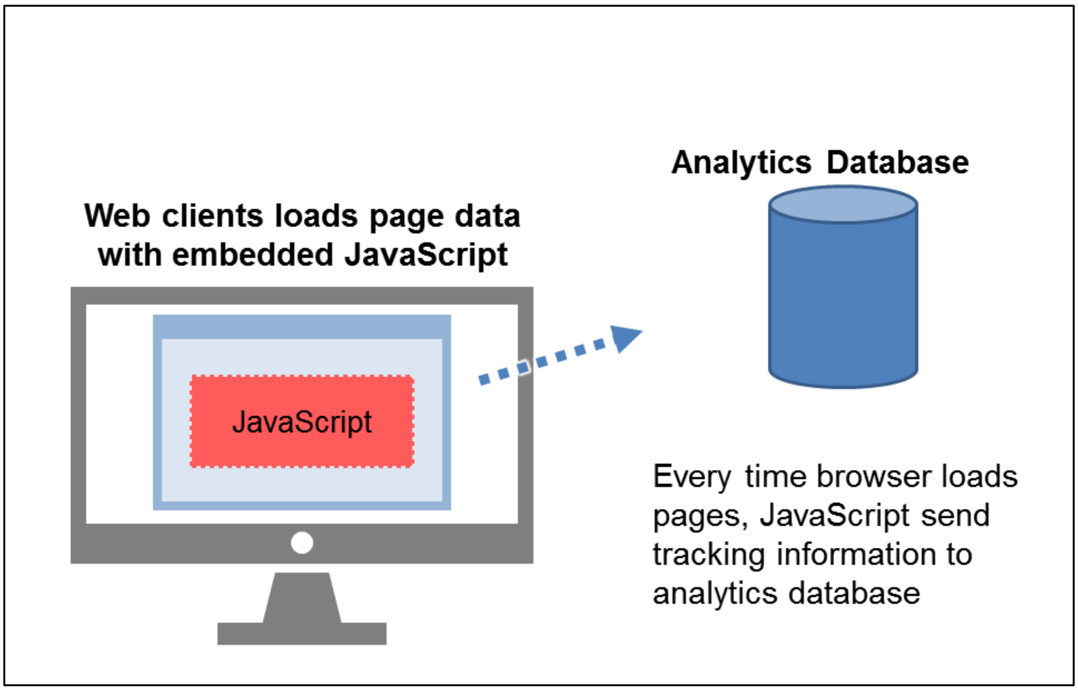


Figure 1. Web Beacon Basic Image

Figure 2 shows Web analytic technology overview. This figure shows generation of technology and functions by each category.

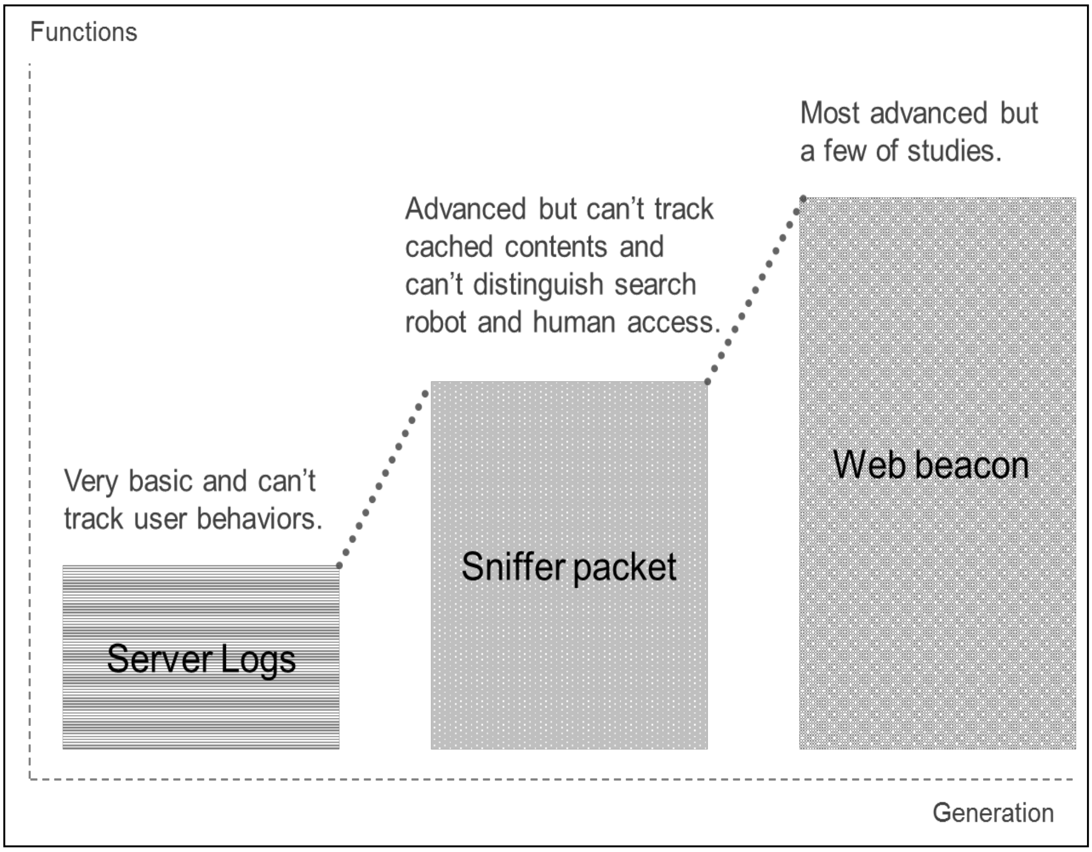


Figure 2. Web Analytic Technology Overview

2.2. Web Analytics Trends and Previous Studies on User Behavior

I refer to past studies related to my study and I pick up some major studies in the following. All related studies are shown in Reference chapter.

There were general studies about web analytics. Reference [89] showed study on web mining techniques. Reference [75] proved information visualization techniques were useful for web analytics. Reference [68] presented a framework for understanding web usage patterns from web log files. Another study about web analytic showed a way to utilize web analytic tool to conduct behavioral analysis in [121] and to analyze web user behavior by collecting all web access data for a particular user in [94]. Reference [30] showed investigation on web analytics from security perspectives.

In another study, ethical consideration of collecting web user data as well as its guideline was discussed in [50]. Reference [77] demonstrated usefulness of web analytics using business to consumer (B to C) case. There was also a research about ecommerce site in [123] showing that there is a way to analyze web access logs and classify users in precision.

There was study about log file analysis for ecommerce site in [1]. Reference [39] identified factors affecting continuous usage of web site through web log data. In [122] web access was used to analyze sequential access pattern mining for web personalization. They showed Analysis of access logs (analytics) is important for building a website which is user-friendly for visitors and which can provide many marketing data to the site owner. The background and reasons for the importance of access log analysis in web marketing, and a case example of removing services that analysis found to be unpopular from a website is summarized in [28].

There were also web metrics study in B to B domain. In reference [113], they conducted a study about B to B web site from branding perspectives. Furthermore, they used clickstream data to analyze B to B web site performance and concluded that web analytics can be applied in a B to B domain in [118]. In addition, there are studies about design, usability of web sites. In one study, cognitive phenomenon was used to analyze user attention in [33].

The study in [65] investigated web form evaluation approach by utilizing user questionnaire, electroencephalogram and eye tracking for more user-friendly web form. In a different study, process improvement approach was taken to improve design and usability of web form in [108].

However, there was no study done for in-depth B to B web analytics methodology for such a critical web conversion metric and also web form registration and factors of web user registration.

2.3. Characteristics to be Considered in B to B Web Analytics

B to B can be defined as commerce transactions between businesses, such as between a manufacturer and another manufacturer, between a manufacturer and a wholesaler, or between a wholesaler and a retailer. It has a variety patterns for it. Compared to B to C web analytics, B to B web analytics have the following three characteristics:

i. In many cases, the buyer is not the same person as the web user. Therefore, it is important to analyze all the users from the same company or organization as a single unit. That can be stated as B to B to C web analytics, not simply B to B.

ii. The goal of visitors to the web site is often not only to make a purchase. Main conversions can be downloading a file, making an e-mail subscription or inquiring online. Therefore, relationship between providers and customers are more important than in B to C.

iii. It is rare for a user to complete their goal within a single session. In most cases, users require multiple sessions spread out over a long period to complete their goal.

iv. In B to B more logical process and value-oriented decision can be used than in B to C situation in which there could be more emotional.

Considering the above characteristic, I study on web analytics just for B to B industry.

2.4. Chapter Summary

This chapter firstly summarizes web analytic technology with three generation as server log type, packet capture type, and web beacon type. Next, I sorted out web analytics trends and past studies. Also confirmed we do not have many studies on B to B related web analytics compared with B to C or e-commerce related. I listed B to B features to be considered for analytics like that the buyer is not the same person as the web user, that the goal of visitors to the web site is often not only to make a purchase or, that it rare for a user to complete their goal within a single session. These three sections are basic premises in this report and all findings and proposed methodologies are given based on these premises.

3. B to B Web Analytics Framework

3.1. Path Analysis

Paths analysis is said as web behavioral analysis in another word. We can see user process flow in web site and we can utilize analysis to optimize web usability and to know user requirements. When path analysis is performed for a B to B site, two types of paths are found in our survey. Figure 3 shows the page transition models.

One type is “roving” model, which is typically seen for example on product information pages. The user visits several different product information pages while absorbing information. Furthermore, for roving type it is necessary to identify core pages, for example by looking at which pages have low exit rates, or which pages are entry pages for the site, in order to analyze the characteristics of the roving behavior.

Figure 4 shows exit rate and number of entrance analysis. You can find core page in roving type of pages with this method. As normal behavior model, one of core page features is to have more entry of visitors and exit rate is lower because it is highly prioritized page in search and many touch points and it can navigate visitors to sub-pages. Figure 5 shows an example of roving model analysis.

This example shows that the product family page is the core page. Users navigate in a roving path centered around this page, so we know we need to improve its indexability and improve links out to pages that we want users to visit. In addition, the user behavior is different between user segments.

No referrer access is normally from e-mail or bookmarks. As an example, we can see Environmental info page over e-mails can be an entry more easily and less an exit than through search engine (like Google). For roving type, indicators such as time spent on page and average number of page views per page need to be measured.

The other type is “straight-line”, where the user goes towards a goal, such as making a download or purchase, in a straight line. We can consider that straight-line model is connected to final user achievement, which is described as conversion in later sections. In addition, it can be assumed that it is especially easy for users to exit a straight-line path when they encounter an error message or other trouble during the registration process.

Figure 6 shows straight-line behavior type example. We need to check each step analysis for straight-line behavior type. This straight-line behavior type related analysis methodology is given in Chapter 5 of this report.

Also as common analysis we need to see overall picture of user behavior as a site or particular page set like an A product family related pages. In this case, Path thickness evaluation is effective because we can find user’s favorite route with this approach.

Figure 7 shows path thickness analysis. In this diagram, you can see how many users navigate as site aimed and how many users exit from expected route. With this approach, you can see site bottleneck in user behavior.

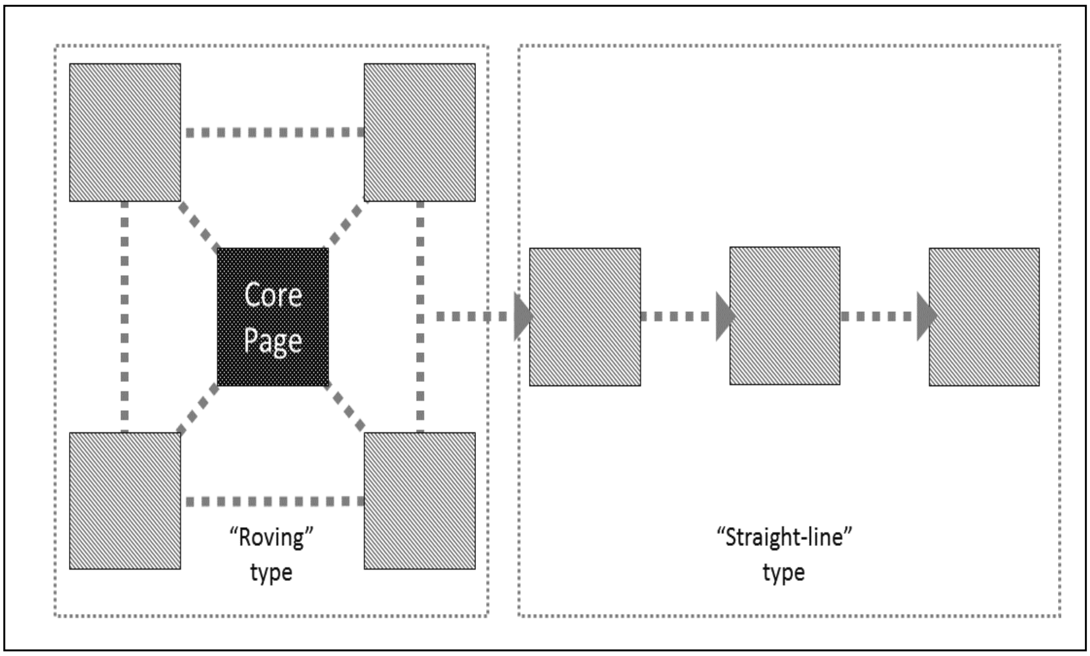


Figure 3. Page Transition Model

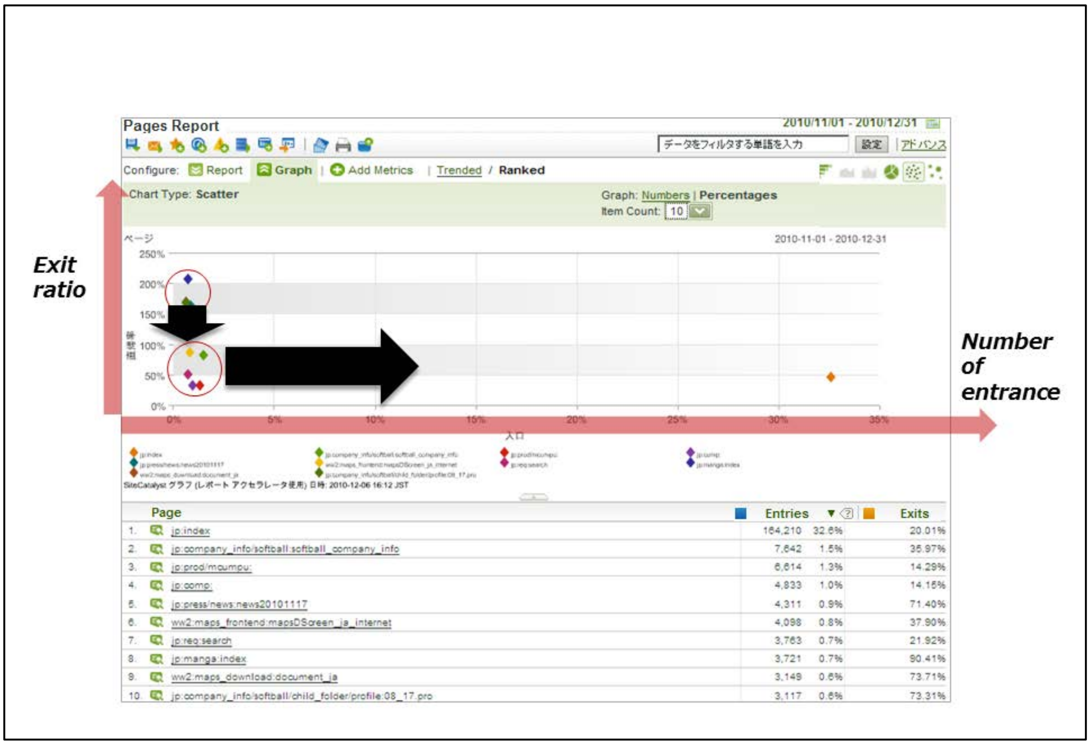


Figure 4. Exit Rate and Number of Entrance

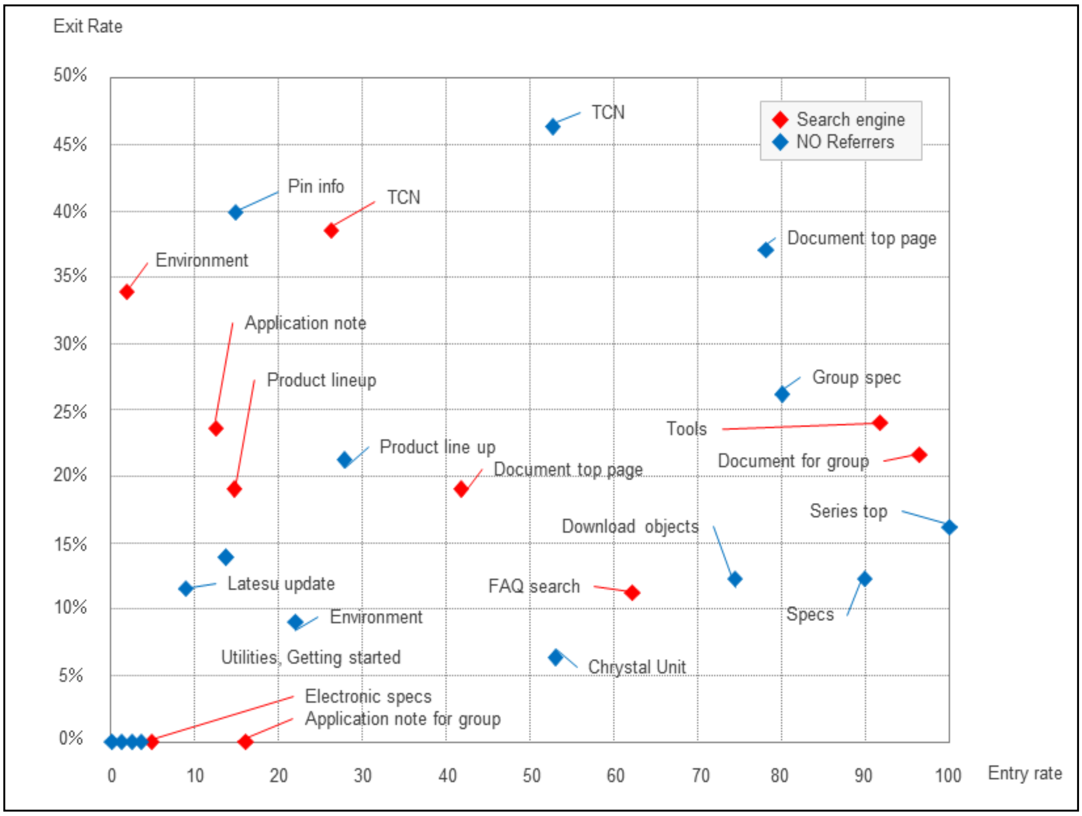


Figure 5. Roving Model Analysis

Figure 6. Typical Straight-line Behavior Type Example

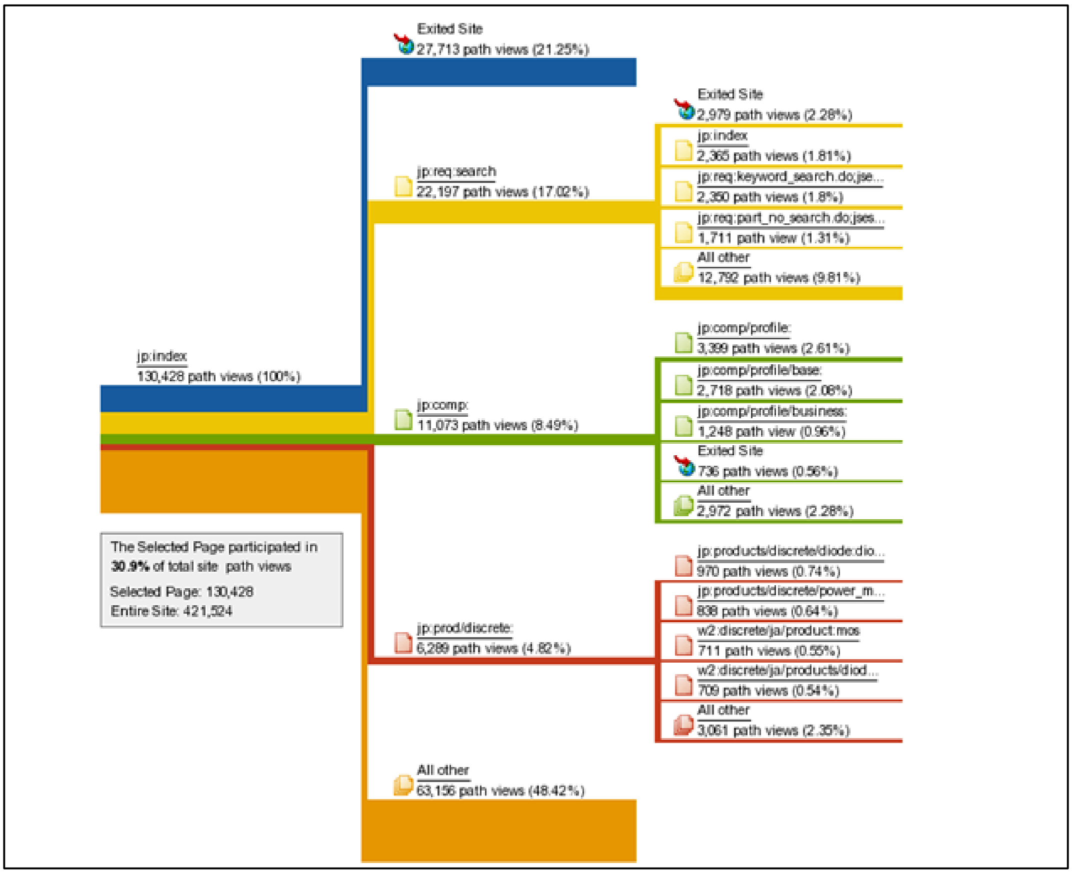


Figure 7. Graphical Path Thickness Analysis

3.2. Analysis on Participation to User Conversion

In web analytics area, “Conversion” is one of important keywords. Conversion means to convert web site visitors into purpose-achieved users. Figure 8 shows a conversion funnel to on-line purchase. Web user process for B to B web site is usually defined and described as a funnel or a pipeline. Like a real funnel, the process involve sifting through a large amount of visitors in the beginning, identify which of intermediate process are keys to users, then turning these visitors into customers at the end of the funnel. In this example how many users reaches on-line purchase as final achievement. Conversion concept can allow us to examine which page has value to user success in sales funnel and see what needs to be done to increase conversion percentage or rate. Figure 9. Shows fall-out analysis. "Fallout analysis is a subset of path analysis, looks at "black holes" on the site, or paths that lead to a dead end most frequently, paths or features that confuse or lose potential customers. In this example, you can see all step’s lost percentage and pages or processes you need to improve. Fallout is a reverse of conversion analysis and we can find issues in user navigation.

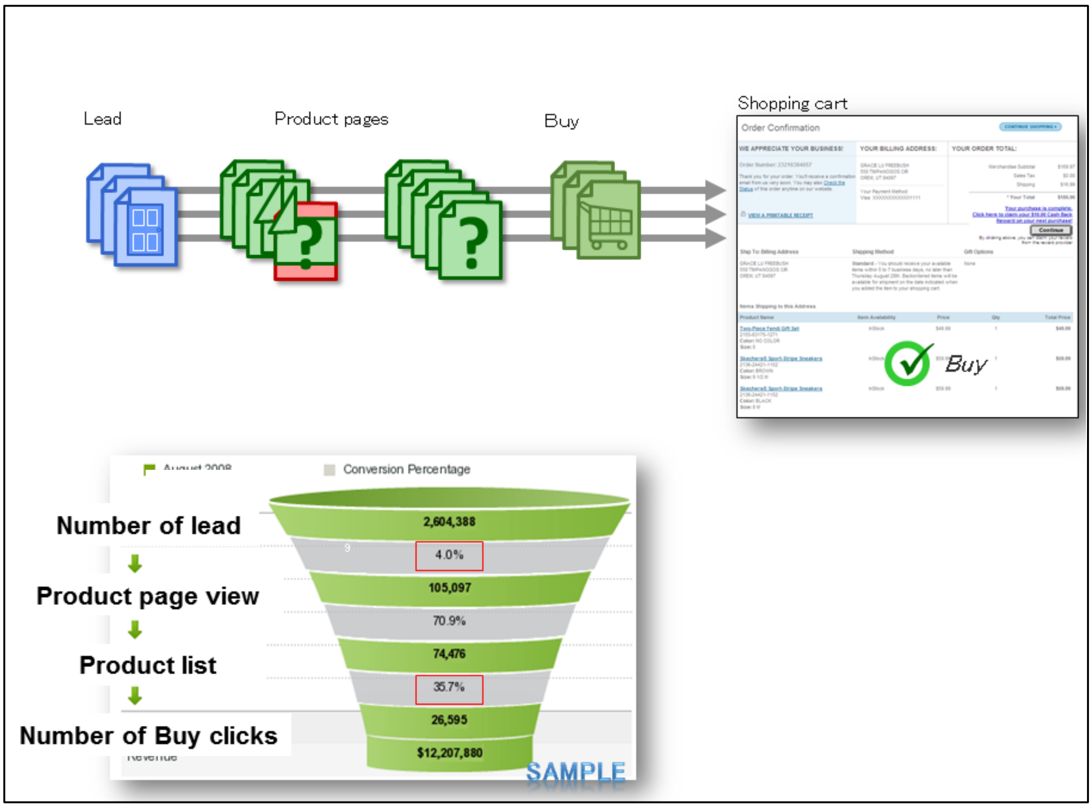


Figure 8. Conversion Funnel to Purchase

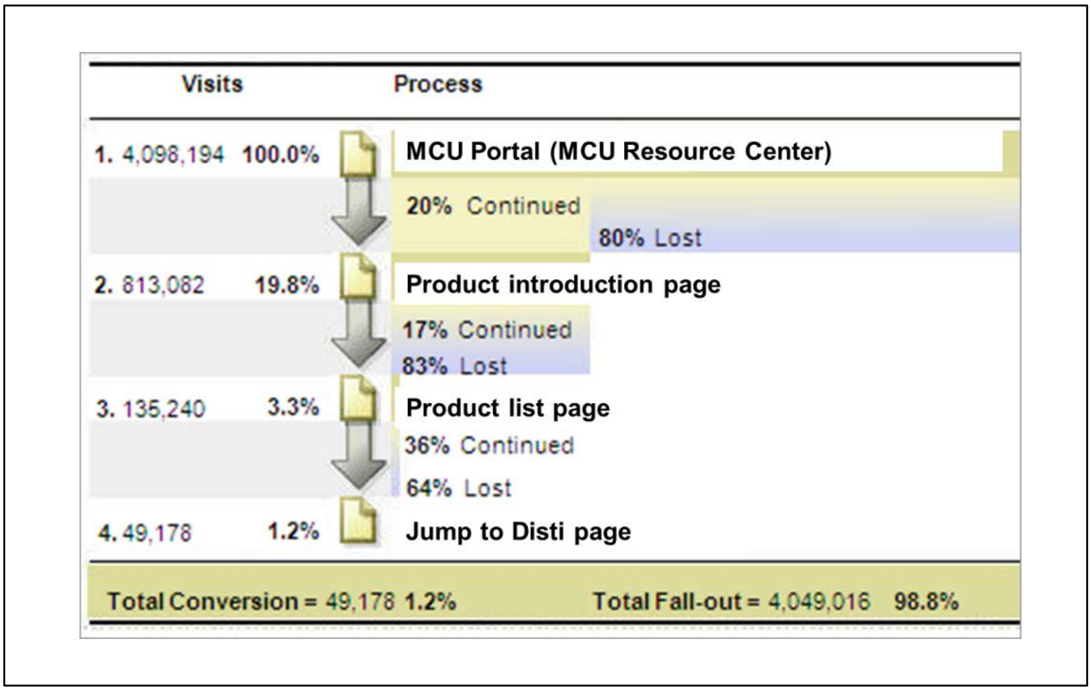


Figure 9. Fall-out Analysis

In addition, Conversion rate is a key metrics on how much rate the page can produce conversion. “Conversion rate” is calculated as the following.

```
Conversion rate = Number of achievements/visitors
```

Otherwise,

```
Conversion rate =Number of achievements/page views
```

In this report, the second formula is used essentially without any special statement. Taking a Buy action as a conversion (user goal), I propose a way to analyze which function contributed the most to the conversion (participation analysis).

Sometimes it might be to download brochures and other times it might be to buy products on web site.

In participation analysis, measurements were only performed over the same session for a B-to-C site and we easily find studies. However, this is not a very effective way of analyzing a B-to-B site. Figure 10 shows an example of a B-to-C conversion.

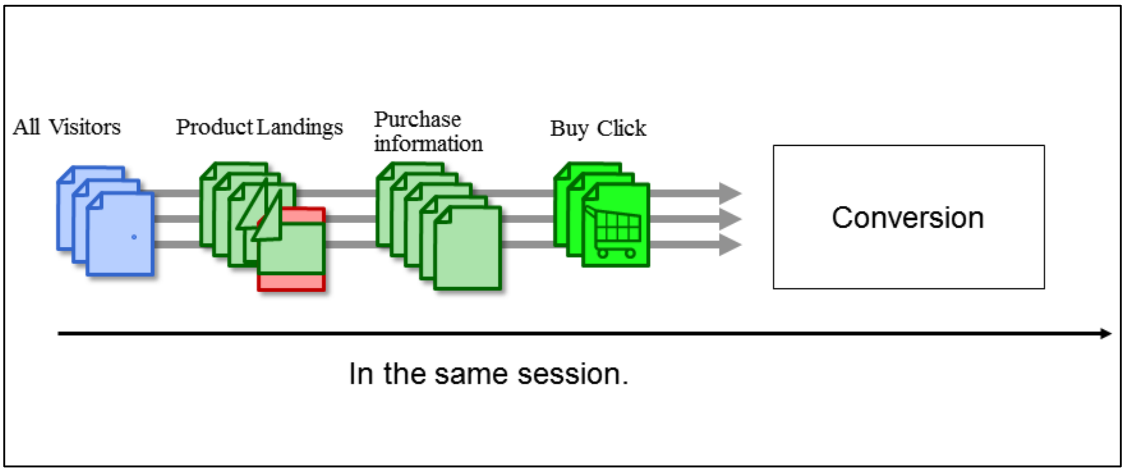


Figure 10. Typical Conversion on B to C site

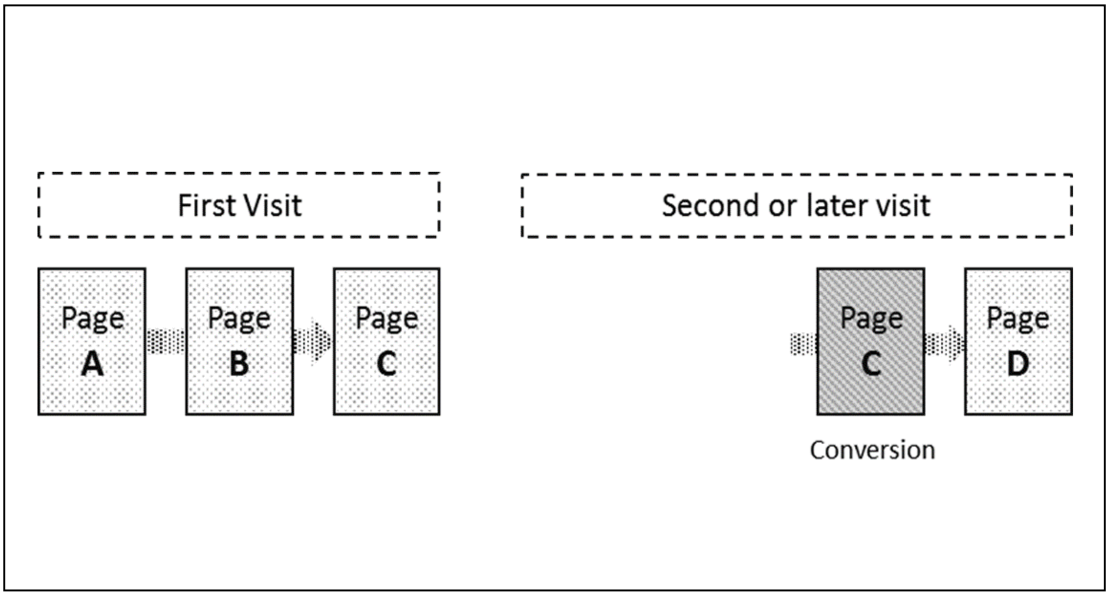


Figure 11. Over Session Conversion

On the other hand, it is rare for a conversion to be completed in a single visit to a B to B site. There are many examples of conversions completing over the course of multiple visits over several weeks or in some cases several months. Figure 11 shows over session conversion image.

In the manufacturer industry, the so-called Lead (How to reach site), Find (search for a product or solution), Try (prototype using a product), and Buy (purchase) model is typical, and in many cases this process is completed over the course of several visits. There are also many cases where the website is used as a supplement up to a certain point, and then the actual purchase is made via a sales agent in an offline channel. Thus, I would like to recommend measuring participation over the long term. This will allow us to know what the user did during a long time span before the actual purchase. It is possible to measure it using cookie.

The example in figure 12 example of participation analysis. It shows which pages a user who pushed the Buy button on the website used over multiple sessions, or in other words participation analysis. We analyzed the participation of user characteristics (How did the user come to the site?) and user behavior on the site (What pages did the user view? What site functions were used?). In this example, we can see that conversions can be strongly attributed to the search engine, and behavior analysis shows that conversions can be strongly attributed to parametric search. Therefore, participation rate needs to be carefully examined by user purposes.

Contribution rate by user behavior for lead action

Items	Mail click	Google/Baidu search	Bookmark / Type	Visit at first time
Contribution rate	3.8%	54.8%	48.2%	23.8%

Contribution rate by user behavior for find/try action

Items	MCU Top Page	Keyword Search	Parametric Search
Contribution rate	18.3%	18.4%	24.1%

Figure 12. Example of Participation Analysis

If conversion occurs at during the second visit, we cannot see participation on pages with “In a session approach”. Visitor participation attributed across multiple sessions can be effective for B to B sites. As shown in figure 11, conversion can occur at during the second and more visit in B to B web site due to its business model. Differently from B to C industry, we need to use participation metrics over sessions should be used using cookie technology. Table 1 shows the difference of two models of participation. In this table, you can see difference between participation-with-over-sessions-concept model and participation-with-single-session-concept model. In this example for only participation with single session concept can make page C and D participation. I recommend participation-with-single-session-concept model for B to B if we need to consider long-term customer relationship.

Table 1. Participation Concept Models

Viewed page	At session	Participation with over sessions concept	Participation with single session concept	
			1st Session	2nd Session
A	1st session	Yes	No	No
B	1st session	Yes	No	No

Viewed page	At session	Participation with over sessions concept	Participation with single session concept	
			1st Session	2nd Session
C	2nd session	Yes	No	Yes
D (Conversion happened)	2nd session	Yes	No	Yes

In addition, as “lead” activity which means to navigate people to web site there are many aspects like advertisement, bookmark, external links and e-mails. As most popular “lead” activity, e-Mail related studies are described here. Please refer to figure 13 tracking recode method

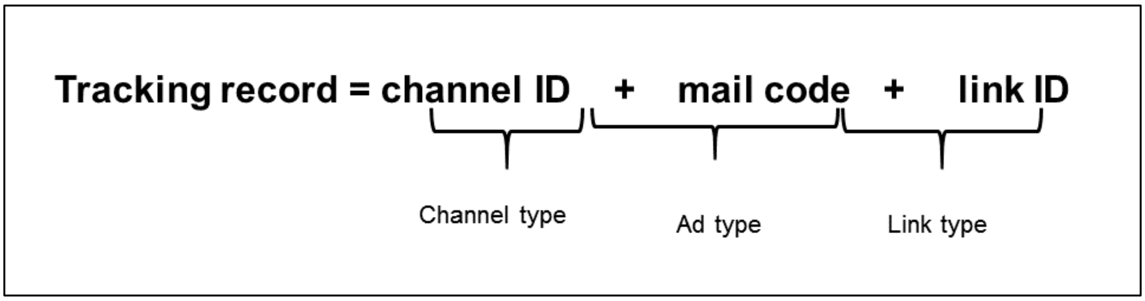


Figure 13. Tracking Recode Method

All channel for lead activity should be identified with this method and entire site tracking by lead channel is possible. The following is an explanation of each item.

i. Channel type: Distinguishes from which channel the visitor came from. For example, e-mail was shown as EMM, listing as PPC, and banner as BNM with abbreviation.
ii. Ad type: Distinguishes the type of advertisement in relation to the channel. For example, if it was the e-mail sent on September 10, 201５, it will be shown as 20150910, and listing on Google as GGLE.
iii. Link ID: Distinguishes the link contents of each Ad type. For example, if it was an announcement e-mail of a campaign, it will be shown as CAMP, and if it was a keyword of the listing, the recognizable abbreviation of the keyword will be shown.

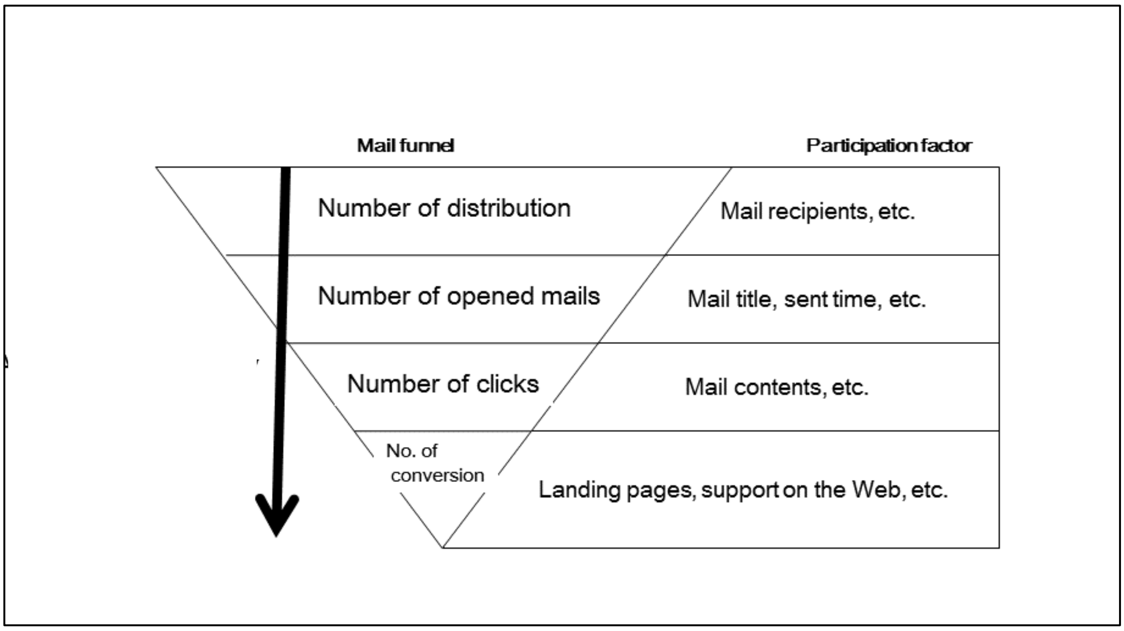


Figure 14. Email Path Analysis Method

Please refer to figure 14. This is proposed tracking number as e-mail path analysis method.

i. Number of distribution: How many mail letters are distributed? Who are the recipients?
ii. Number of opened mails: How many mails were actually opened?
iii. Number of clicks: How many recipients clicked on the links in the mail letter?
iv. Conversion number: How many visitors from the mail letters reached to the conversion?

3.3. A/B testing and multivariate testing

Although web analytics can be used to improve usability, normally it is difficult to compare two user interfaces at the same time. For example, when comparing data before and after a change is made, analysis may be difficult due to seasonal or other factors for the two periods. It is effective to use JavaScript to divide users into two equal groups for measuring conversions (inquiry, etc.).

We carried out A/B testing. In this A/B testing, the same test experience will be displayed as long as visitors do not delete the cookies of the web browser and the test experience to be displayed randomly and equality for first time visitors. Using this we can compare two interfaces over the same time period, collect data until the t-test is satisfied, and determine which interface was more effective. By using more than two (A/B) patterns, multivariate testing can be carried out for many variations and combinations. Rather than a simple page comparison, an accurate conversion comparison can be performed (for example, testing the effectiveness of different combinations of banner and position). This is extremely useful for site optimization.

Furthermore, I found that testing of users from specific regions can be performed by expanding these A/B testing and multivariate testing techniques, and then, after effective designs and combinations are identified, the techniques can be used to use to display only the effective design for access from specific regions, in what is called targeting. Figure 15 shows an example of A/B testing, and figure 16 shows conversion results with A/B test. In this case, I tried to show same product roadmap in meaning with A pattern (recipe) and B pattern (recipe) and see the conversion rate. In this case, A pattern produced more conversion.

Figure 15. An Example of A/B Testing

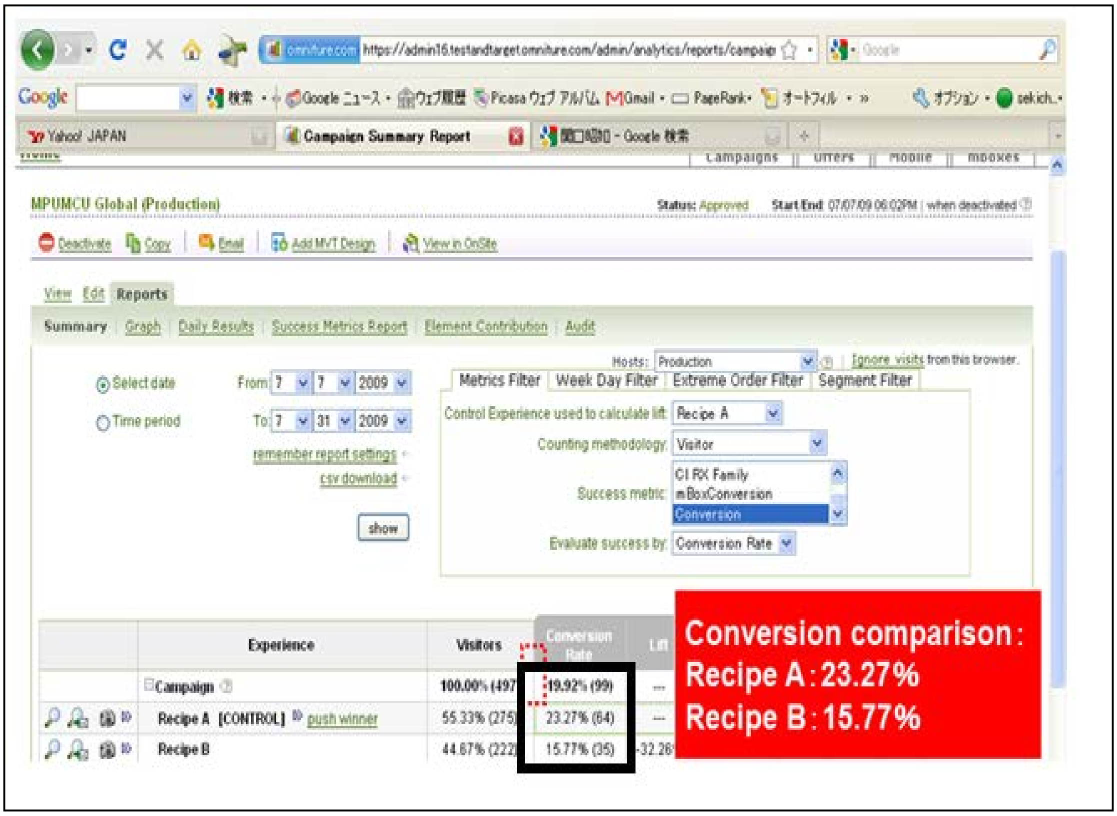


Figure 16. Conversion Results with A/B Test

3.4. Customer Journey and User Registration

When we consider customer journey for B to B manufacturer customer we need to think of both on-line activity and off-line activity because they do not care about distinguish and need both. For example, they need to attend events and seminars if necessary and they may need to get information and required resources in web site. In on-line activities, I created the following model majorly with web site.

i. Find: User finds solutions/product information
ii. Explorer: User checks product features/functions/characteristics/availability/price and learns about company/products/trends/backgrounds.
iii. Try: User evaluate or try to use products and product environment
iv. Buy: User purchase products or their related goods
   However we need to note it is not always on-line but also off-line is more popular in B to B. On-line buy happens especially for small quantity purchase or getting product samples.

v. Maintain: User maintains their service or products after purchase

For B to B web sites, information which requires user authentication to access is more meaningful to analytics than information which can be freely viewed by anyone. The reason is that user profiles and company (organization) profiles can be logged. Although most of the information on a web site can be freely viewed by anyone, key important information requires user authentication to view. More advanced analysis (especially of small and medium-sized companies) can be carried out by analyzing access logs of each authenticated user utilizing cookie technology. Therefore, the hooking contents for user registration are important for users and manufacturers. Figure 17 shows user registration in B to B web site customer journey.

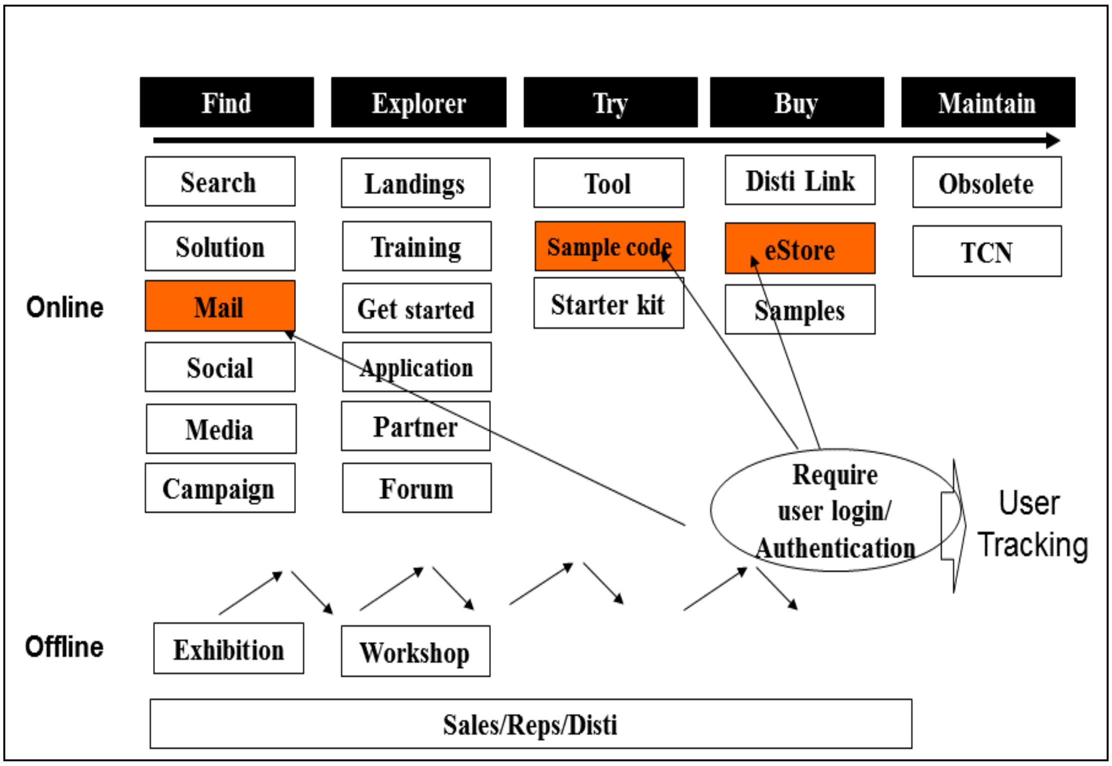
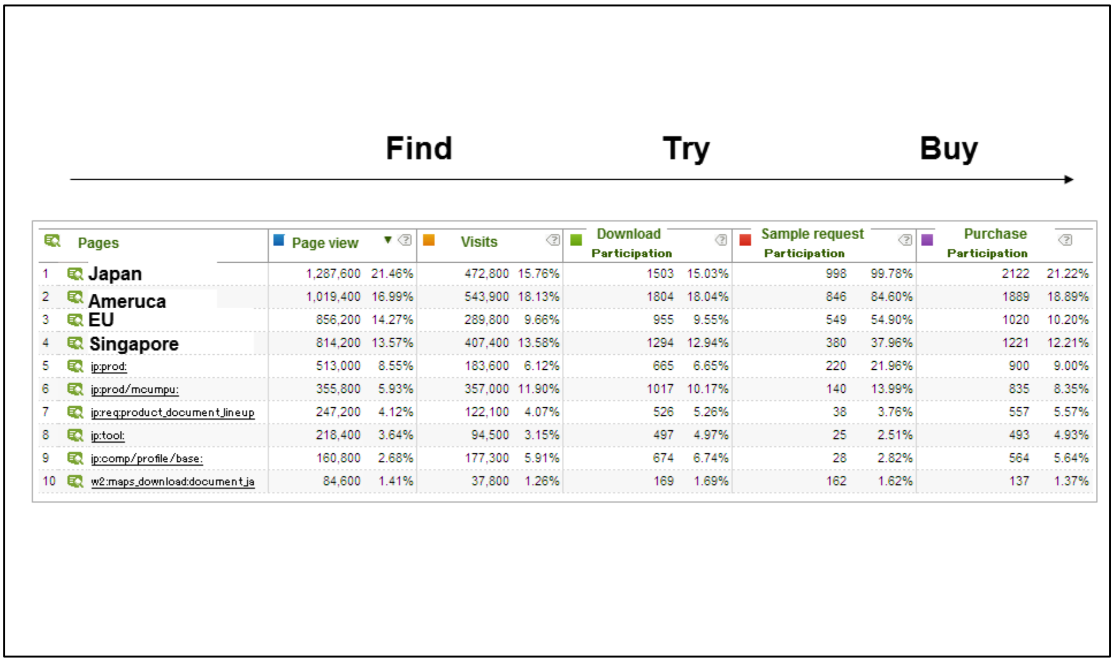


Figure 17. User Registration in B to B Site Customer Journey

Figure 18 shows actual data mapping example to customer journey model. When we define the process for key action for each journey element, we can see how many visitors access this touch point and you can see data in consequent way.



	Pages	Page view		Visits		Download Participation		Sample request Participation		Purchase Participation	
1	Japan	1,287,600	21.46%	472,800	15.76%	1503	15.03%	998	99.78%	2122	21.22%
2	Ameruca	1,019,400	16.99%	543,900	18.13%	1804	18.04%	846	84.60%	1889	18.89%
3	EU	856,200	14.27%	289,800	9.66%	955	9.55%	549	54.90%	1020	10.20%
4	Singapore	814,200	13.57%	407,400	13.58%	1294	12.94%	380	37.96%	1221	12.21%
5	jp:prod:	513,000	8.55%	183,600	6.12%	665	6.65%	220	21.96%	900	9.00%
6	jp:prod/mcumpu:	355,800	5.93%	357,000	11.90%	1017	10.17%	140	13.99%	835	8.35%
7	jp:req:product_document_lineup	247,200	4.12%	122,100	4.07%	526	5.26%	38	3.76%	557	5.57%
8	jp:tool:	218,400	3.64%	94,500	3.15%	497	4.97%	25	2.51%	493	4.93%
9	jp:comp/profile/base:	160,800	2.68%	177,300	5.91%	674	6.74%	28	2.82%	564	5.64%
10	w2:maps_download:document_ja	84,600	1.41%	37,800	1.26%	169	1.69%	162	1.62%	137	1.37%

Figure 18 Customer Journey Mapping to Access Data

3.5. B to B Web Analytics Framework Model

As I mentioned chapter 1 I have two following premises for values of web analytics for B to B manufacturer companies. (1) Improve and optimize the site in user behavior and (2) Use in marketing activities like as knowing user requirements. Considering web analytic framework with two premises structured approach is required. As top down approach, breakdown steps are required from these two premised analytic purpose. I came up with the framework model from two premised purposes into next level business requirement, then into next requirement like site/page requirement, and finally into five methods i.e. path analysis, conversion analysis, segmentation (Targeting), and user registration analysis. Also in B to B web site, we should run PDCA (Plan, Do, Check, Action) cycle with this methodology. That overall structure is shown in Figure 19. Path Analysis, conversion and participation analysis, A/B test/multivariable test, segmentation and user registration analysis is key to concrete analytics.

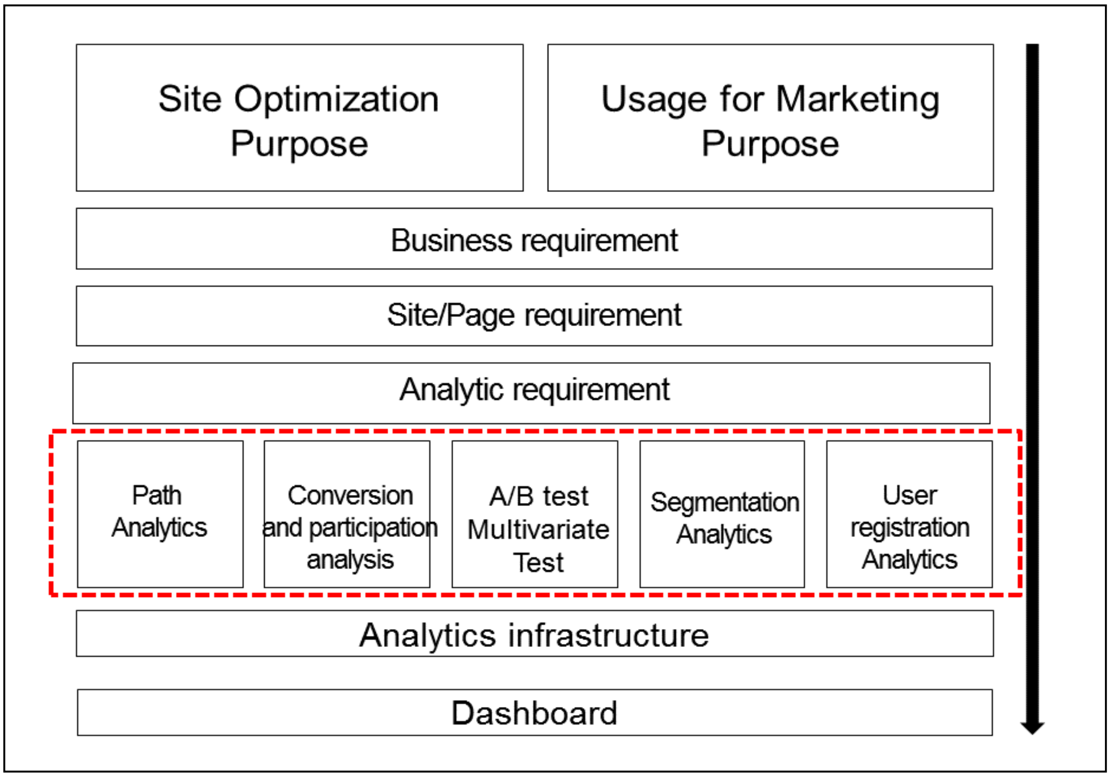


Figure 19. Web Analytic Framework for B to B

Figure 20 shows actual break-downed web analytic requirement and implementation steps. In this example based on two purposes analytic requirement and implementation are made. Firstly, we should clarify B to B manufacturer goal of on-line activity, and next define business requirement, and next drill down actual web site requirement or particular page requirement. Finally based on this structured break-down web analytic requirement should be created.

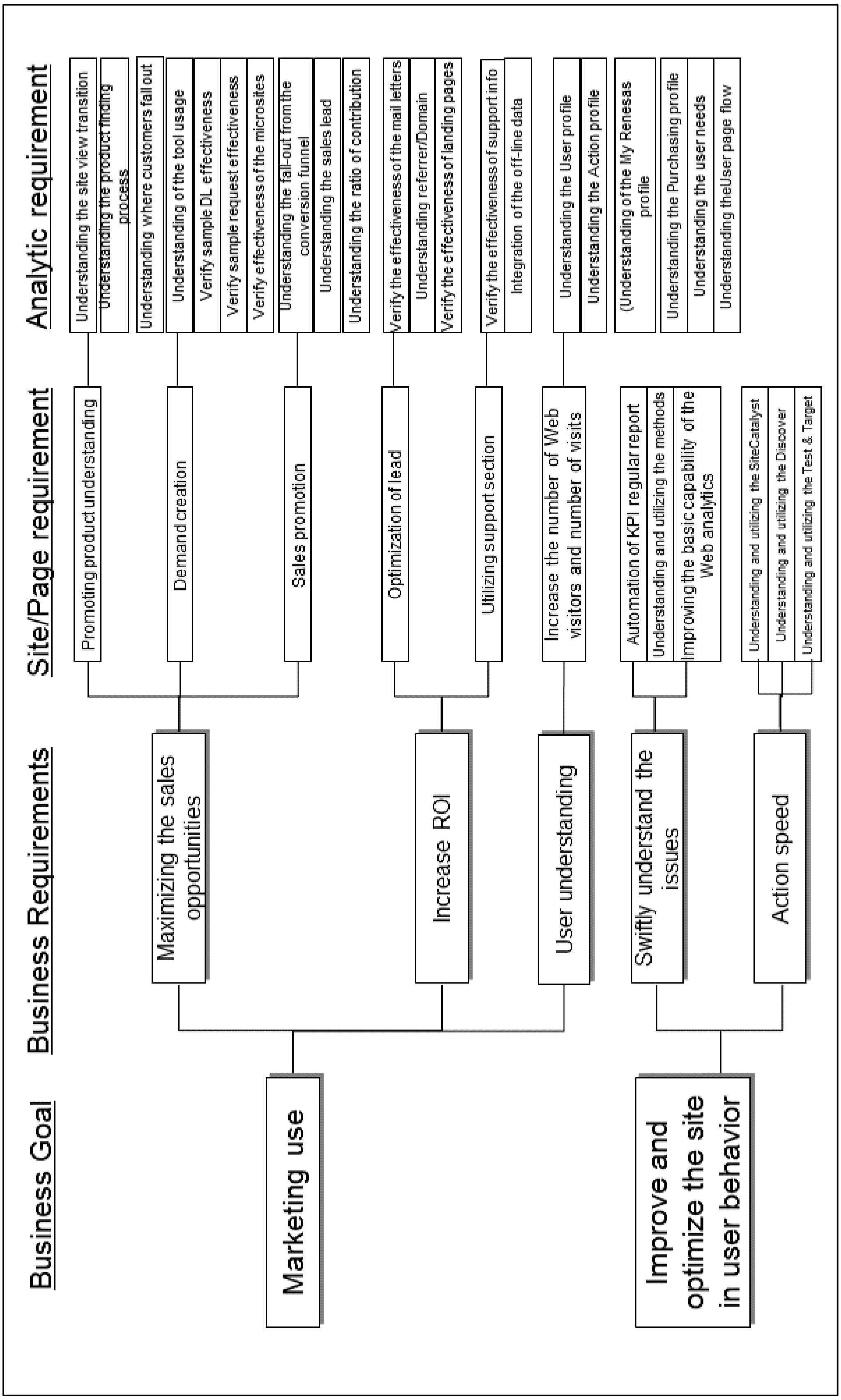


Figure 20. Actual Breakdown Web Analytic Requirement and Implementation

Figure 21 shows business requirement mapping to KPI. Based on business requirement web analytic methodology should be decided. Finally, KPIs that we should track is decided accordingly. In this example, six business requirements decide methodology as fall-out, page flow, external campaign, segment, product, and entry path. Figure 22 shows four phases of analytics.

Actually, we need some steps to do all methodology. I recommend using 4 phases considering maturity. Phase 1 is about understanding of users and touch points. Phase 2 is to optimize and to make marketing. Phase 3 is automation and creating dashboards. Phase 4 to realize customer relationship management.

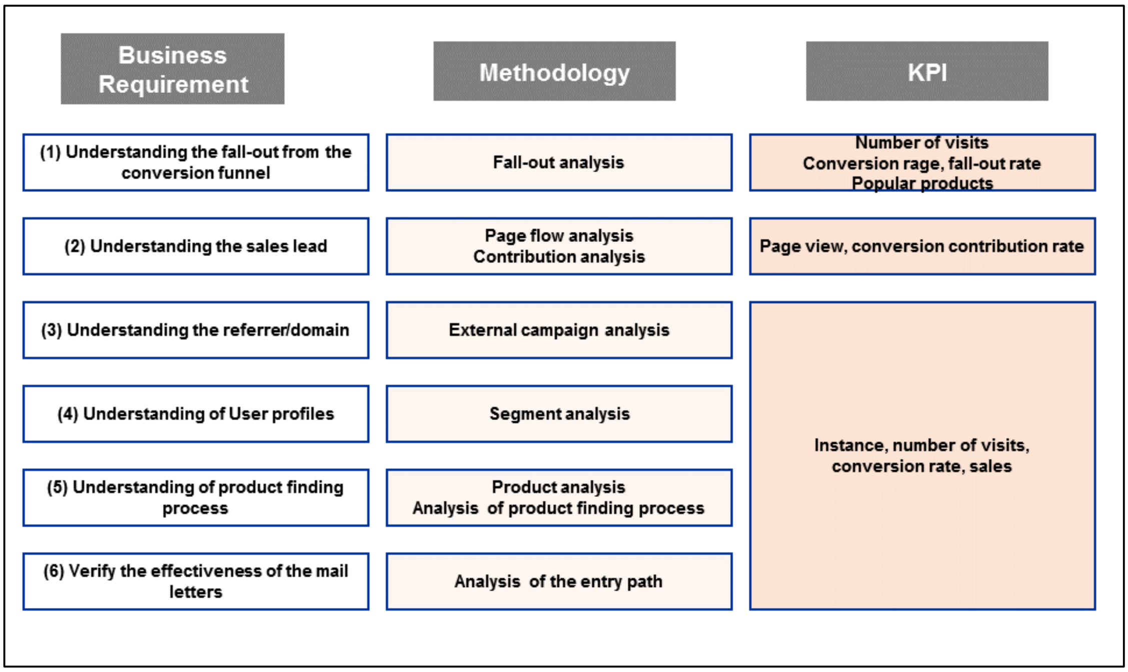


Figure 21. Business Requirement Mapping to KPI.

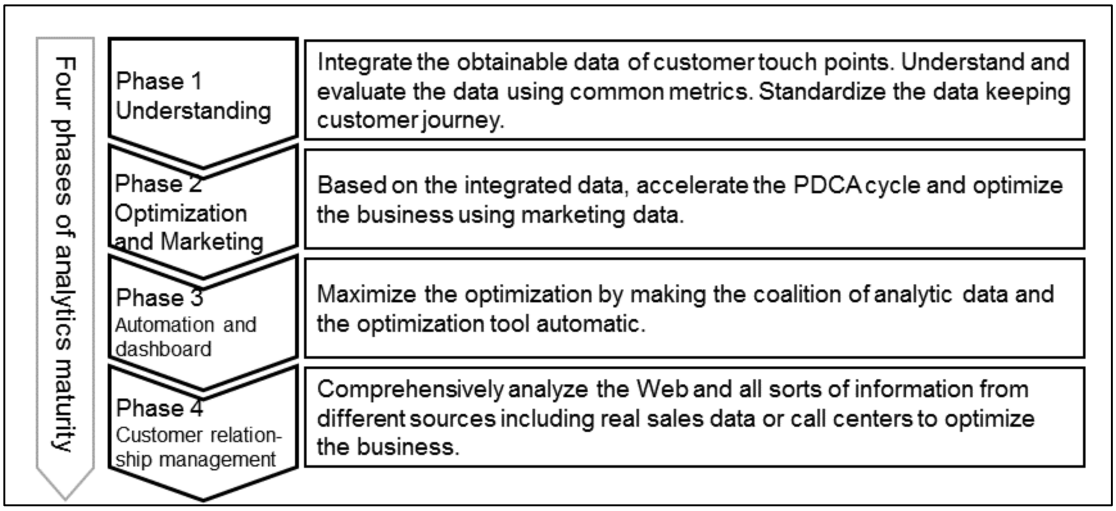


Figure 22. Four Phases of Analytics.

Figure 23 shows Web analytics dashboard example for KPIs. This allows audience or web people concerned to understand status of web site or business itself.

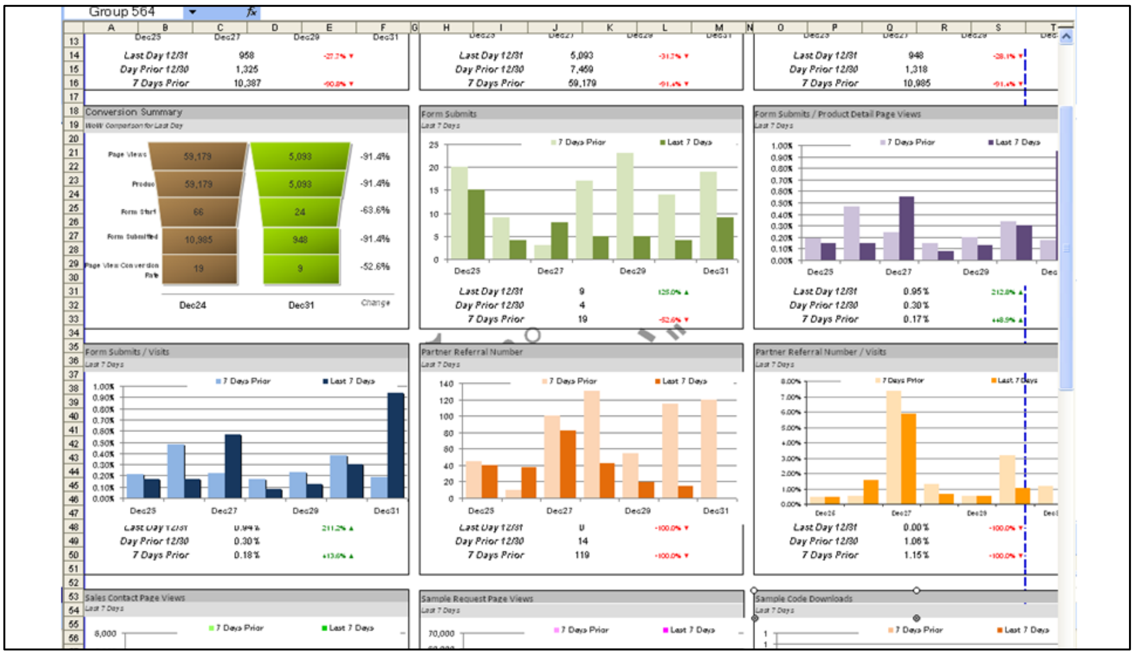


Figure 23. Dashboard Example

In addition, dashboards can be broke down showing more specified insights. Table 2 shows KPI dashboard by product category. You can see the product itself performance and popularity on web site by products. It helps for markers, company executives, and web operation understand them. Table 3 shows dashboard by visit times and it can help us know customer loyalty for web site.

Table 2.　Dashboard by Product Category

Products	Revenue		Order Number		Page view		Order /Page view	Exit Rate
A	113,100,00	18.85%	23	15.12%	1,571	15.17%	1.52%	2.38%
B	99,420,000	15.57%	21	18.85%	4,231	18.51%	0.50%	9.33%
C	94,740,000	15.79%	42	9.52%	3,221	9.94%	0.51%	0.51%
D	77,280,000	12.88%	55	12.96%	1,879	13.51%	0.30%	0.30%
E	48,360,000	8.06%	32	6.76%	639	6.39%	0.36%	0.36%

Top 5 product families web performance by product /month (2011/Sep.)

Table 3.　Dashboard by Visit Times

Visit times	Visitors		Product section page view		Downloads		Purchase	
1st visit	984000	82.00%	1684200	80.20%	50	4.20%	1	0.08%
2nd visit	132000	11%	270900	12.90%	78	6.50%	1	0.12%
3rd visit	84000	7%	198450	9.45%	172	14.30%	8	1.20%
4th visit	165840	13.82%	266070	12.67%	340	28.30%	14	2.20%
5th visit	97080	8.09%	140700	6.70%	527	43.89%	52	8.21%

Segmentation analytics is discussed in chapter 4. User registration process is also described in Chapter 5. Once we get user information with registration process web analytic, makes it possible to track user behavior like in table 4 and it helps manufacturers understand each potential customer business needs and nurture them to purchasers or customers.

Table 4. Personal Tracking with User Registrations

To User ID	Personal Interest (CorpExFairs)	Personal Interest (A Products)	Personal Interest (B Products)	Personal Interest (C Products)	Total Clicks	Top page	Catalog	Product family	tools	Video
45283	1	1			548	53	14	10	46	9
23189	1		1		119	20	3	7	7	1
39128					94	5	3			
34647					80	3			1	
31582	1	1	1	1	70	8	1		3	1
43755					59	8				
43374					51	5				
9718	1	1		1	41	3		1		
37134	1	1	1		35	4	1			
47219				1	32	4				
35432					30	3		2		
48328					16	7	3		1	
43369					14	2				
20810	1		1		11	2			1	
26219	1	1	1	1	11	3	3	1		

3.6. Basic KPI and Trials of Page Dwell Time Approach

In this section, I pick up key metrics and discuss an additional metric called "Page dwell time" Metrics means indicators which manufacturer company should tracks. In this section, I call it KPI (Key Performance Indicators).

Typically, the following metrics are often used for KPI.

- Page view
- Unique users
- Visits per user
- Conversion rate

Page view is the most often used but it is hard to see true user flow with a single metric. One example is when we have many pages reaching a final target page that is called the conversion page (conversion from "visitor" to "purpose achieved"); total page view count is high, but most pages could be unnecessary for users.

In this case, we need to look at page dwell time as well as the page view metric. Page dwell time is the time length that users stay per page. Note that it is different from site dwell time.

Similar metric "Site dwell time" is the length of time that elapses from the first moment a web user enters a particular website until the time that user leaves that website.

Presumably, a combination of page view and page dwell time can be an important metric set for measuring user visit behavior. On top of that, page dwell time is sometimes discussed in web analytic academic studies, but there are very few studies on the combinations and also few on B to B related studies.

The following items are expected to use page dwell time with.

- **i.** Combination of page view and page dwell time can allow more detailed analytics of page role and the gap between designed user behavior and actual results.
- **ii.** It helps categorize the page type, like index page or article page, which users actually read through.
- **iii.** Possible to evaluate page value related to user conversion with dwell time, and score pages for each conversion.

Firstly, I had a look at relationship between dwell time and page view in the sub-section 1) and then I spent some time in studying relationship between dwell time and conversion participation in two ways in the sub-section 2).

1) Consideration on relationship between dwell time and page view

In B to B manufacturer site, assumed page categories are the followings.

- Index type page: It is a kind of table of contents for child pages.
- Product catalog type page: It has lots of information with standardized format and often used.
- Article type page: It is article type page and page length has many variations.
- Transit type page: It is one of steps in procedure like user registrations.
- Conversion page: It is final destination page and it can be different in site purpose. Sometimes it can be purchase page and other times it can be download page.

Let us see the page dwell time by content type.

a) Product catalog page analysis.

Especially product catalog page among the above listing has much volume typically in manufacturer web site. In product family site, I picked up 200 pages and each page has information, which can be volume of one page in printed A4 size. Firstly, we need to review the overview of the dwell time data. The figure 24 shows the relationship between page view and page dwell time. We see most of users take about one minute to stay a page. The page access over 2 minutes is not often and even if we have it is with very a few page views.

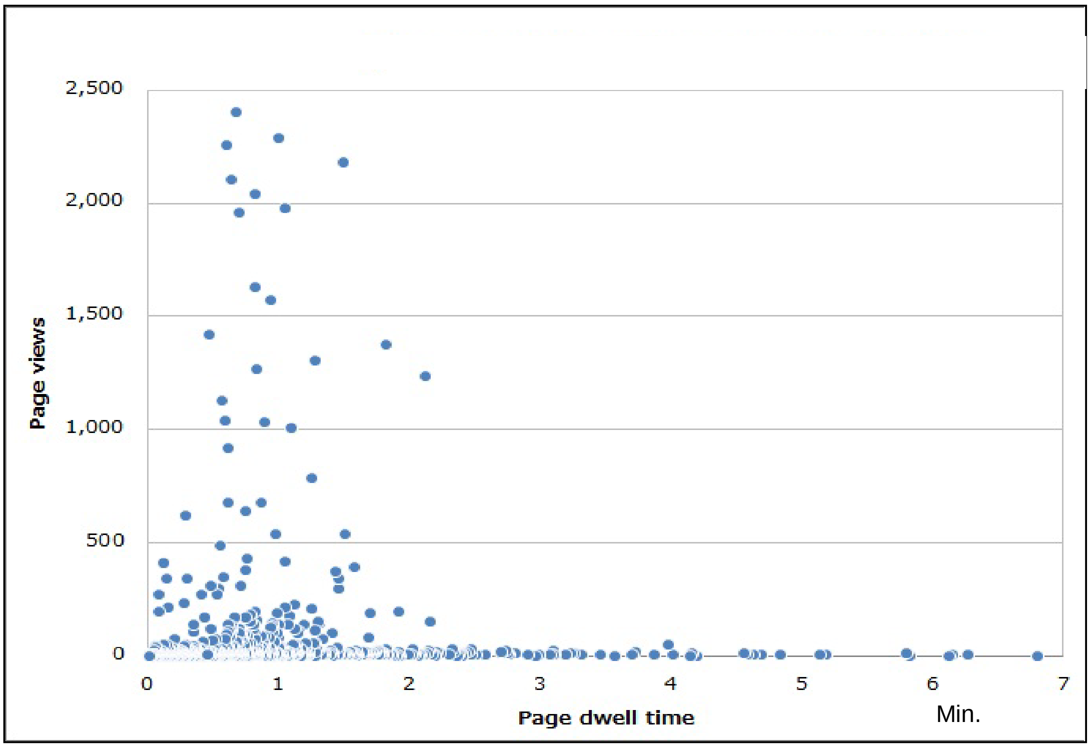


Figure 24. Typical Relationship between Page View and Dwell Time

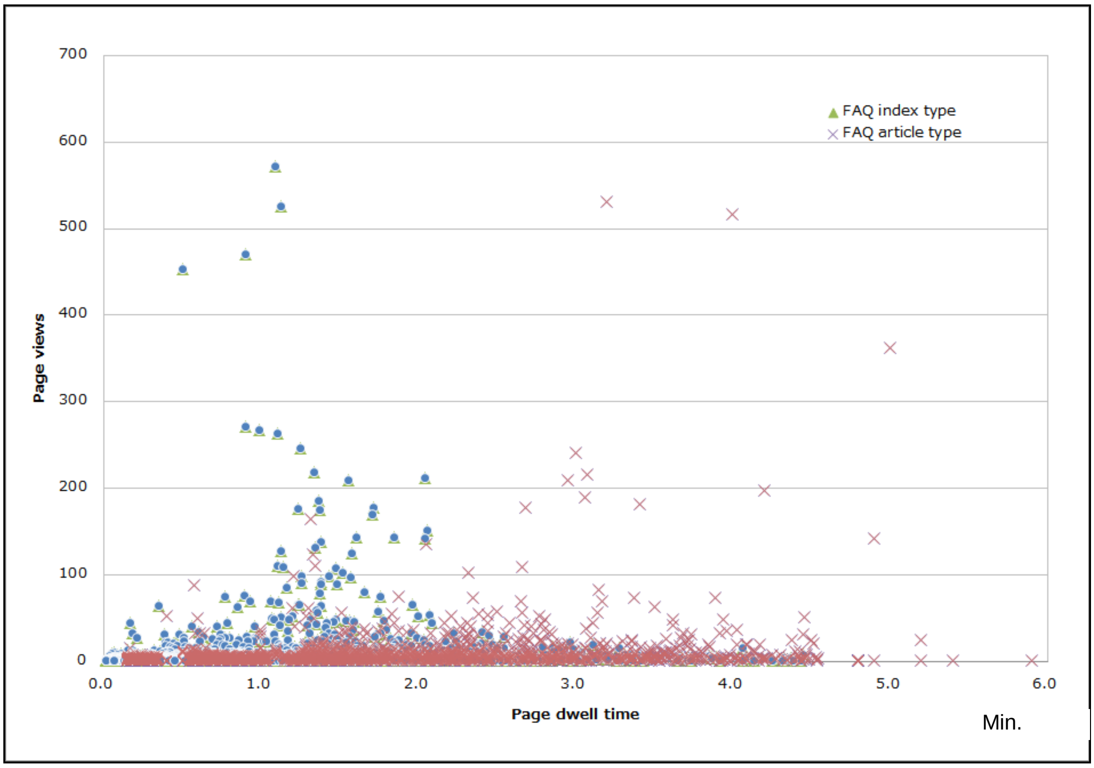


Figure 25. Dwell Time on Index Type Page and Article Type Page

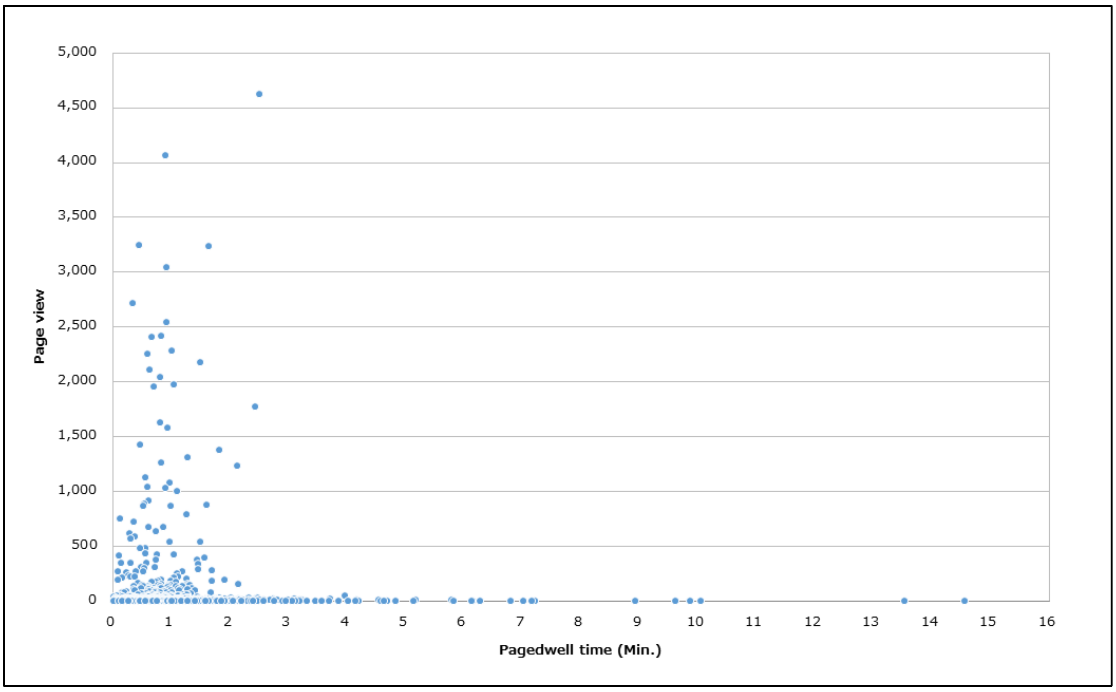


Figure 26. Dwell Time on FAQ Page

Table 5. Page Dwell Time and Other Metrics Correlation

	Pageview Total	Pageview with Mobile	User Home page	Referer instance	Reload number	Entrance page	Exit page	Page Dwell time	Visit number	Page depth	Site dwell time	Seach	Direct exit
Pageview Total	1												
Pageview with Mobile	0.5272038	1											
User Home page	0.750041	0.4696294	1										
Referer instance	0.7811711	0.5025217	0.9456842	1									
Reload number	0.7193369	0.1996858	0.2278476	0.2475605	1								
Entrance page	0.7927243	0.5231201	0.9549046	0.9933446	0.2497228	1							
Exit page	0.8705033	0.4979453	0.6635086	0.6455429	0.640713	0.6614431	1						
Page Dwell time	0.9280234	0.463587	0.6934811	0.6762167	0.7285878	0.6898824	0.962755	1					
Visit number	1	0.5272038	0.750041	0.7811711	0.7193369	0.7927243	0.8705033	0.9280234	1				
Page depth	−0.050759	−0.182886	−0.062372	−0.065274	0.0518002	−0.078237	−0.098956	−0.059182	−0.050759	1			
Site dwell time	−0.025101	−0.037602	−0.010677	−0.010528	0.0870223	−0.015531	0.1039972	0.103323	−0.025101	−0.202961	1		
Seach number	0.7737555	0.5074825	0.9420431	0.9922438	0.2166049	0.9970024	0.6363458	0.6613573	0.7737555	−0.079327	−0.017539	1	
Direct exit	0.7031807	0.4815703	0.76514	0.8194475	0.2931913	0.8254412	0.6824724	0.6787416	0.7031807	−0.158412	0.1268658	0.82134	1

a) Trends on article type page and index type

The following is the results of metrics on pages that are designed for reading like FAQ (Frequent Asked Question). FAQ page has two types of pages. One is index type that consists of lists of FAQs with short description of each FAQ and another type is article that is an actual FAQ page. Typically, the information volume of actual FAQ page is two or three pages long in A4 paper.

In fact, actual FAQ page is longer than FAQ index page in dwell time. Index type is 0.9 min average and article type average is 2.5 min. Please refer to the Figure 25. Page dwell time is dependent on page type. Figure 26 shows general trends on all FAQ related pages.

2) Relationship between dwell time and conversion participation

In this sub-section, I will talk about two aspects of relationship between page dwell time and conversion. One is on dwell time of participation pages to conversions and another is dwell time of just previous pages to conversions.

a) Dwell time of participation pages to conversions

As a reminder conversion means user’s final goal in web activity. In typical B to B market area, conversion target of web site does not necessarily mean purchase. Objects download like program source, document download, and sales inquiry can be conversions sometimes. Especially user registration for the web site is one of the most common conversion.

Considering the relationship between conversion and page dwell time, I checked dwell time of pages passed through by users to destination page, which brings conversion. We call these pages “Conversion related pages” I had originally expected conversion related page have longer dwell time because these pages are related to user decision. However, seeing the statistics we can say conversion related pages dwell time is not longer than all pages average.

It seems users go fast across pages into final conversion generally. Especially even user registrations which mostly commonly used by B to B customers does not have longer time. Please refer to the Figure 27.

Most contributed page (product/mpumcu/index.html) has 0.42 min. as average dwell time. It is much shorter time than general average. It shows that users pass through pages with short time taken and finally reaches goal page.

Page name	Dwell time (min.)	Page view	Product lineup	Parametric search	Registration	Buy
products/mpumcu/rl78/index	0.46	30,250	1,378	2,738	255	601
products/mpumcu/index	0.42	46,478	4,450	3,767	575	599
products/mpumcu/rx/index	0.37	32,978	1,182	1,855	220	450
products/mpumcu/r8c/index	0.41	21,193	1,080	2,227	205	387
products/mpumcu/superh/index	0.53	30,912	1,042	2,475	349	347
products/mpumcu/rl78/rl78g1x/index	0.31	8,399	360	992	29	285
products/mpumcu/rl78/rl78g1x/rl78g13/index	1.04	8,111	459	1,177	31	262
products/mpumcu/rx/rx600/index	0.50	14,402	330	932	143	234
products/mpumcu/rl78/rl78g1x/rl78g14/index	0.96	4,012	201	734	10	232
products/mpumcu/rx/rx600/rx621_62n/index	0.91	9,200	181	668	54	212
products/mpumcu/rl78/rl78g1x/rl78g12/index	0.80	3,545	210	805	31	177
products/mpumcu/78k/index	0.51	10,848	1,281	1,285	205	175
products/mpumcu/r8c/r8c3x/index	0.49	7,601	263	887	34	160
products/mpumcu/h8/index	0.47	11,186	750	685	381	135
products/mpumcu/v850/index	0.50	12,611	797	743	118	130
products/mpumcu/rx/rx200/index	0.51	8,494	348	568	52	130
products/mpumcu/superh/sh7080/sh7080/index	0.83	1,720	74	284	21	112
products/mpumcu/superh/sh7216/sh7216/index	0.85	2,231	68	377	1	100
products/mpumcu/r8c/r8c2x/index	0.33	3,277	114	436	36	97
products/mpumcu/rx/rx200/rx210/index	0.96	6,787	306	621	32	95

Figure 27. Dwell Time on Conversion Related Pages (Top 20 by Registration Conversion)

Page name	Partner Link Click	Parametric Search	User registration	Group Page View	Keyword Search	Inquiry Form Complete	External Link Participation	External Link Click	Download Files	Application Note Page View	Vsitors	page view	Dwell time (min.)
index	9	44	39	277	2,838	7	106	106	130	130	7,143	15,192	0.48
req/search	3	86	1	2,703	3,323	0	149	149	670	670	4,017	12,934	0.82
products/mpumcu/index	3	23	0	229	272	0	16	16	57	57	3,243	6,735	0.55
products/mpumcu/rx/index	0	6	0	581	35	0	17	17	105	105	2,036	4,754	0.64
products/mpumcu/superh/index	5	27	0	967	72	3	19	19	75	75	1,808	4,124	0.64
products/mpumcu/rl78/index	0	20	0	799	56	4	13	13	91	91	1,728	4,011	0.64
req/part_no_search	3	0	20	1,211	664	1	81	81	435	435	956	3,838	1.56
products/index	0	0	0	58	183	0	12	12	15	15	1,876	3,273	0.40
req/keyword_search	0	13	1	345	1,346	0	23	23	79	79	1,041	2,811	0.96
request	3	6	30	412	100	0	55	55	269	269	1,331	2,751	0.88
products/mpumcu/r8c/index	0	12	0	177	50	0	6	6	52	52	1,247	2,603	0.51
products/mpumcu/rx/rx600/index	3	5	0	1,520	7	1	2	2	67	67	960	2,156	0.81
products/tools/index	1	0	0	22	52	0	23	23	25	25	1,115	2,136	0.48
products/mpumcu/v850/index	1	4	0	269	31	0	5	5	40	40	746	1,574	0.60
products/mpumcu/h8/index	0	0	0	441	24	0	0	0	14	14	734	1,486	0.49
products/tools/ide/hew/index	8	0	0	73	20	0	22	22	27	27	593	1,418	0.80
products/mpumcu/78k/index	0	7	0	308	29	0	1	1	32	32	667	1,370	0.59
req/product_document_lineup_child	1	4	0	553	11	0	4	4	120	120	859	1,304	0.78
products/mpumcu/h8s/index	0	0	0	213	16	0	0	0	13	13	556	1,216	0.52
products/mpumcu/rx/rx600/rx621_62n/index	1	0	0	789	13	0	39	39	90	90	603	1,164	0.88
products/mpumcu/rx/rx200/index	0	5	0	666	4	0	4	4	35	35	513	1,086	0.85
products/mpumcu/rl78/rl78g1x/index	0	2	0	726	10	0	3	3	63	63	592	1,078	0.73
products/mpumcu/rl78/rl78g1x/rl78g13/inde	0	0	0	769	35	0	27	27	123	123	551	1,043	0.87
products/tools/ide/cubesuite_plus/index	0	0	0	58	20	0	24	24	117	117	470	1,019	1.11
req/sample_code	1	0	2	10	16	0	0	0	250	250	194	1,009	2.17
products/mpumcu/m16c/index	0	0	0	172	16	0	1	1	20	20	558	983	0.54
products/mpumcu/rx/rx600/rx63n_631/index	1	0	0	624	20	0	46	46	95	95	501	961	1.04
products/mpumcu/rh850/index	0	0	0	153	15	0	4	4	35	35	496	876	0.77
products/tools/emulation_debugging/onchip	0	0	0	44	7	0	71	71	219	219	390	849	1.15
products/mpumcu/r8c/r8c3x/index	0	3	0	568	7	0	1	1	21	21	396	836	0.61

Figure 28. Dwell Time and other metrics on Conversion Related Pages

Figure 28 shows dwell time and other metrics combination we can utilize.

Please refer to table 2. “Buy through distributors” is one of the B-to-B market conversions. I expected the pages related to “buy” conversions to have longer dwell time than the total average (around 1 min.) because this conversion could take some decision-making. However, this average time for this conversion is 0.84 min., which is shorter than the total average. This is one of the characteristics seen with B-to-B sites.

I assume users had already decided to buy product due to a previous or earlier visit to the website so when they purchase they go straight to the purchase without examining product specifications. I checked the pages that were used the most for conversions. Table 6 shows page dwell time average only in page conversion related like purchase urging page (Buy page). In Table 6, No. 3 and No. 4 were the common important conversions for this manufacturer. For the purpose of user registration conversion in No3, software download pages are highly ranked. They make up 34 pages among the top 100 pages and the next most numerous are sample code/document download pages. This is understandable for a B-to-B manufacturer’s website. Also for No. 4 “Buy” conversion, the most common conversion related pages are product spec pages. They make up 20 pages among the top 100 pages.

As a result, we can assume users examine the product specifications even if only for a short time. In manufacturer web site, typically, product information has the most of pages and this area is the highest in access because most of users need manufacturer product related information at manufacturer site.

Table 6. Overall Statistics of Dwell Time on Conversion Related Page

Unit: minutes

No.	Conversion related page	Average time	Maximum time	Minimum time
1	Product lineup list page	1.01	2.29	0.35
2	Parametric search results	0.99	2.38	0.09
3	User registration	1.01	2.51	0.09
4	Buy	0.84	2.24	0.08
5	All pages related to conversion	0.95	3.02	0.03

b) Dwell time of just previous pages to conversions

I made analysis for all of conversion related pages in the previous sub-section and next we focus on the only previous page of conversions. In the previous sub-section generally we can say dwell time of all conversion related pages are not so long compared with general average but we need to check the time of just previous pages

As we stated earlier in this report one of important conversion is user registrations. When we see the dwell time data of previous pages mostly used, it is 1.79 min. average and longer than general average. We assume many users select the proper downloaded files carefully before user registrations. In addition, one note is that the secondly mostly viewed page is the explanation page of user registration and disclaimer. It is 0.38 min. and relatively low. We see most of users pass through this page but they do not take longer time with it. It is another one of key findings.

The average dwell time of previous pages of conversions is 1.13 min. Our original expectation was longer than normal dwell time average. However, it is almost same as other pages even if it is soon before conversions.

Figure 29 shows dwell time of previous page of user registration conversions.

Page name	User registration	Vsitors	page view	Dwell time (min.)
support/downloads/download_results/C100(	51	212	517	1.79
support/how_to_use_myrenesas/index	50	34	92	0.38
index	39	7,143	15,192	0.48
support/downloads/download_results/C100(	32	179	384	1.04
request	30	1,331	2,751	0.88
myrenesas/index	26	140	244	0.50
req/part_no_search	20	956	3,838	1.56
support/downloads/download_results/C100(	19	63	112	1.65
support/downloads/download_results/C2017	19	91	206	1.82
products/soc/usb_assp/document/registrati	18	4	16	0.53
products/tools/ide/cubesuite_plus/downloac	17	221	529	0.55
privacy/index	16	12	15	0.76
support/downloads/download_results/C2006	15	159	268	1.07
support/downloads/download_results/C200(	15	80	156	1.23
products/mpumcu/rx/rx600/rx62t/app_notes	13	51	119	1.42
support/downloads/download_results/C2017	12	17	35	1.32
products/tools/ide/hew/downloads	10	330	793	0.48
products/mpumcu/rx/support	10	84	111	0.71
products/tools/evaluation_software/downloa	9	257	643	0.39
products/tools/evaluation_software/index	9	390	740	0.63

Figure 29. Dwell Time of Previous Page of User Registration Conversions

Page name	Vsitors	page view	Dwell time (min.)	Buy
products/tools/emulation_debugging/onchip	390	849	1.15	72
buy/disti/index	65	98	0.95	53
products/tools/emulation_debugging/onchip	239	536	1.04	35
buy/index	298	430	0.98	18
req/search	4,017	12,934	0.82	11
products/mpumcu/superh/sh7080/sh7080/ir	109	221	0.86	11
products/mpumcu/rx/rx600/rx621_62n/index	603	1,164	0.88	11
products/tools/emulation_debugging/onchip	95	225	0.83	10
jump	76	119	0.67	9
req/part_no_search	956	3,838	1.56	9
products/mpumcu/rx/rx600/rx610/index	154	271	0.79	9
req/ecommerce	43	62	1.32	8
products/mpumcu/superh/sh7216/sh7216/ir	158	305	0.67	8
req/ecommerceTree_search	41	63	1.44	6
products/mpumcu/rl78/rl78g1x/rl78g13/inde:	551	1,043	0.87	6
products/mpumcu/superh/sh7137/sh7137/ir	24	45	1.31	5
products/mpumcu/rl78/rl78g1x/rl78g12/inde:	232	420	0.63	5
req/keyword_search	1,041	2,811	0.96	4
req/parametric_search	296	540	0.92	4
products/mpumcu/superh/shether/sh7619/ir	59	99	0.85	4

Figure 30. Dwell Time of Previous Page of Purchase Conversions

comp/index	Partner Link Click	Parametric Search	User registration	Group Page View	Keyword Search	Inquiry Form Complete	External Link Participation	External Link Click	Download Files	Application Note Page View	Visitors	page view	Dwell time (min.)
index	9	44	39	277	2,838	7	106	106	130	130	7,143	15,192	0.48
req/search	3	86	1	2,703	3,323	0	149	149	670	670	4,017	12,934	0.82
products/mpumcu/index	3	23	0	229	272	0	16	16	57	57	3,243	6,735	0.55
products/mpumcu/rx/index	0	6	0	581	35	0	17	17	105	105	2,036	4,754	0.64
products/mpumcu/superh/index	5	27	0	967	72	3	19	19	75	75	1,808	4,124	0.64
products/mpumcu/rl78/index	0	20	0	799	56	4	13	13	91	91	1,728	4,011	0.64
req/part_no_search	3	0	20	1,211	664	1	81	81	435	435	956	3,838	1.56
products/index	0	0	0	58	183	0	12	12	15	15	1,876	3,273	0.40
req/keyword_search	0	13	1	345	1,346	0	23	23	79	79	1,041	2,811	0.96
request	3	6	30	412	100	0	55	55	269	269	1,331	2,751	0.88
products/mpumcu/r8c/index	0	12	0	177	50	0	6	6	52	52	1,247	2,603	0.51
products/mpumcu/rx/rx600/index	3	5	0	1,520	7	1	2	2	67	67	960	2,156	0.81
products/tools/index	1	0	0	22	52	0	23	23	25	25	1,115	2,136	0.48
products/mpumcu/v850/index	1	4	0	269	31	0	5	5	40	40	746	1,574	0.60
products/mpumcu/h8/index	0	0	0	441	24	0	0	0	14	14	734	1,486	0.49
products/tools/ide/hew/index	8	0	0	73	20	0	22	22	27	27	593	1,418	0.80
products/mpumcu/78k/index	0	7	0	308	29	0	1	1	32	32	667	1,370	0.59
req/product_document_lineup_child	1	4	0	553	11	0	4	4	120	120	859	1,304	0.78
products/mpumcu/h8s/index	0	0	0	213	16	0	0	0	13	13	556	1,216	0.52
products/mpumcu/rx/rx600/rx621_62n/index	1	0	0	789	13	0	39	39	90	90	603	1,164	0.88

Figure 31. Another Reference Data for Previous Page Dwell Time

Please refer to Figure 30. Even if purchase is important and bigger decision for users the average dwell time is 0.97 min. and it is not long. This is the same trend as conversion related page time that I stated in previous sub-section. Figure 31 shows another reference data which supports figure 30 and we have similar trends.

3) The relationship between text volume and dwell time

One of potential factor related dwell time is page volume. Pages have different size of information and dwell time of users can depend on page size.

Page volume can be measured by text size in HTML (Hyper Text Markup Language). Refer to the Figure 32. Text size is not much related to dwell time. This can be the feature of B to B type web site. Probably dwell time can be more related to page type or conversions. I need to study more on page type relationship with dwell time in details in further studies.

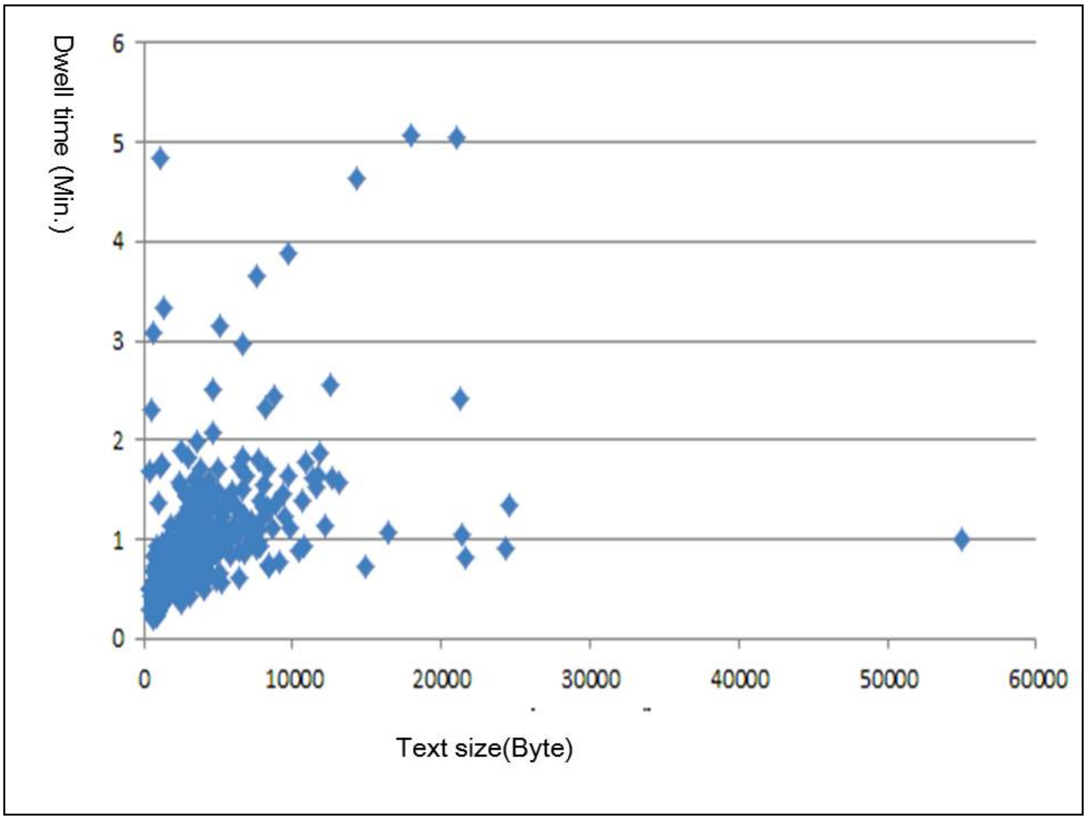


Figure 32. Relationship with Dwell Time

c) Technical issues on page dwell time tracking

The following items are open issues and I need to consider when I analyze data.

- The last page when users exit cannot be tracked at all due to web beacon and http protocol characteristic.
- When new tab in browser is used for clicking the captured data can be wrong because user may keep it alone in this tab and browse pages in different tabs.
- As general aspect, some users keep opening pages for a while. Therefore, we need to remove some abnormal length data.

We need to take care of these items when we check data.

We had originally expected a conversion related page to have longer dwell time because these pages are related to user decision. However, looking at the statistics we can say that the dwell time of conversion related pages is not longer than the average for all pages. It seems that users generally go quickly across pages into final conversion. In particular, even user registration pages, which are mostly commonly used by B-to-B customers, do not have longer dwell times.

Also “buy through distributors” is one of the B-to-B market conversions. We expected the pages related to “buy through distributors” conversions to have longer dwell time than the total average (around 1.1 min.) because this conversion could take some decision-making. However, this average time for this conversion is 0.84 min., which is shorter than the total average.

3.7. Chapter Summary

I tried to clarify B to B web site framework Analytics especially for manufacturer company in this chapter. I have made some test and findings. At first, I came up with two path-analysis model. One type is “roving” model and another is “straight-line” model. I showed actual analysis example and confirmed it is working. In addition, I showed conversion and participation is important and showed differences of points between B to C and B to B web site analytics. As other aspects A/B test and user registration analysis based on customer journey should be included in the framework. I showed the overall picture of web analysis framework and implementation way. I proposed that analytic implementation should be determined with structured way from purpose to dashboard through major five methods like path Analysis, conversion and participation analysis, A/B test/multivariable test, segmentation, and user registration analysis.

In addition, I examined the web access analytics adding page dwell time on page view as typical key factor in B to B manufacturer site. Although we have technical issues, we can see it is effective and it deserves for further study. Especially page dwell time is much related to various types of conversion in B to B site. Also when we think about website structure improvement, seeing page dwell time can be one of good metrics. We can test usability or expected page flow with the results of dwell time as well as page views.

As one of possibility the page length can be related to dwell time but at a first general study we can't see the relationship between page length and dwell time compared with other factors like page type or conversion contribution.

Typically, the following metrics are often used for KPI.

i. Page view
ii. Unique users
iii. Visits per user
iv. Conversion rate

In addition, I confirmed effectiveness of page dwell time utilization and combination with other metrics.

4. Analytics with User Segmentation

4.1. User Segmentation Model

When we think of usability study in more detail with web analytics method, we need to assume user segments because user behavior can differ by user segmentation. Using some of our surveys, we came up with the user segmentation model shown in Table 7. Generally, it was classified by types as information driven, user environment driven, business relationship driven. Information driven type mostly includes content segmentation. most manufacturer sites, the following are typical content categories and we assume user behavior can be different due to difference in purpose of visit.

- Products
- Solutions
- Support (FAQ or Contacts)
- Download or resources
- Purchase
- Press or news
- Seminar/Training
- User registration/Login

"User environment driven" has two elements as "By time and place" and "By Device type". "User behavior driven" is comprised of "By user referrer"," By visit frequency", and "By user commitment level". "Business relationship driven" has two elements as "By company profiles" and "By industry". I tried each related studies and you can see them in related sections in this report. Unfortunately, I have many "Business relationship driven" related studies but cannot put these studies in this report due to business privacy reasons.

Table 7. User Segmentation Model

Segmentation category		Major segment from web analytics point of view	Related sections in this report
Type	Segmentation		
Information driven	By content category	Viewers of product information versus viewers of investment relations (IR)/company information	Section 4.2
		User seeking to download software versus e-commerce users	
User environment driven	By time and place	Weekday users versus weekend users	Section 4.5
		Midnight users versus business hour users	
		By country/state	
	By Device type	User navigation model can be differed by devices.	Section 4.5
User behavior driven	By user referrer	Users arriving through search engine, by e-mail clicks, or by bookmark/URL typing	Section 3.2 and 4.3

Segmentation category		Major segment from web analytics point of view	Related sections in this report
Type	Segmentation		
	By visit frequency	First time versus second and more frequent users	Section 3.2
	By user commitment level	Registered users versus unregistered users	Section 4.4
Business relationship driven	By company profiles	Focus customer versus unfocused	This part is not included in this report due to privacy issues.
		Large customers versus small customers	
	By industry	User behavior by industry	

In my studies, we saw key contents, which are sometimes called hook contents, which require authentication and user registration to view. Once users register their profiles, they are regarded as committed potential or existing customers and then the manufacturer can contact them within the limits of the privacy policy. In addition, we can say registered users are more interested in manufacturer information than unregistered. In typical cases, an unregistered visitor can be just a visitor and they probably came to the site by chance through a search engine like Google. Registered customers sometimes want to get updates from the manufacturer. We defined processes as Find, Explorer, Try, Buy, and Maintain. In a B to B site, we need to consider offline activity linked with on-line activity because face-to-face sales activity is key to success of business. That is why user registration is the most important and manufacturers urge visitors to register profiles.

4.2. Segment by Content

We observed page dwell time statistics using a frequency distribution chart in this site total access as shown in Figure 33. There is a long-tail type trend and the most frequent page dwell time is from 1 to 17 seconds. We also have many cases with longer dwell time. As a site overall this is the typical trend also seen in past studies.

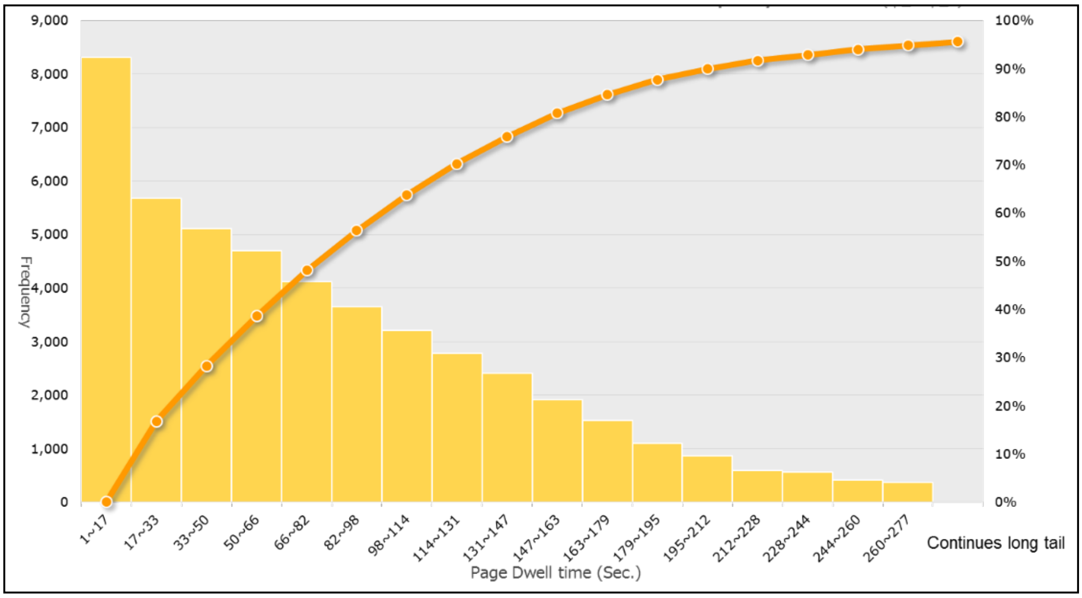


Figure 33. Frequency Distribution Chart

However, if we pick out key landing pages that are mostly important content for both users and the manufacturer, the statistics differ from the general trend. Please refer to Figure 34 and Figure 35. In most cases with key landing pages, it seems the most frequent page dwell time is different from overall site statistics, i.e. long tail. There are two types of content on web sites. One is index type and the other is key landing page content. The overall site statistics include many index pages. Therefore, once we just take key landings we can see the average time and most frequent time easily. We can design web sites or improve page flow using these statistic data. Figure 36 shows product spec page's distribution chart. Figure 37shows press release page's distribution chart. You can see distribution shape is different by content category.

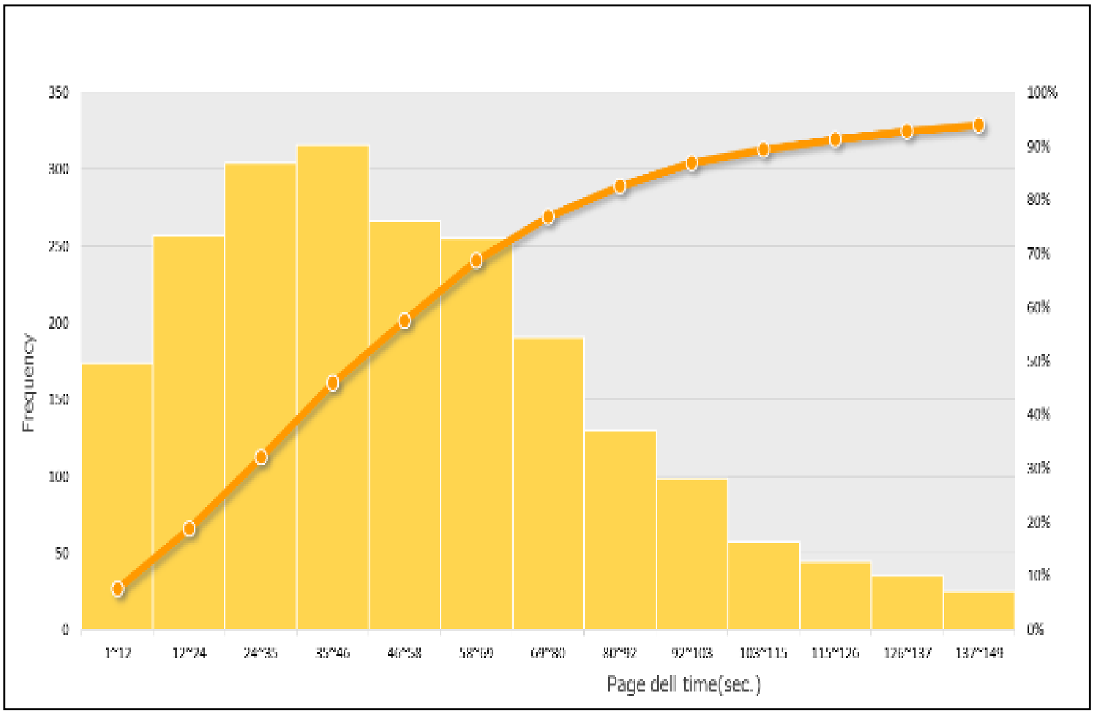


Figure 34. Seminar Page: Frequency Distribution Chart

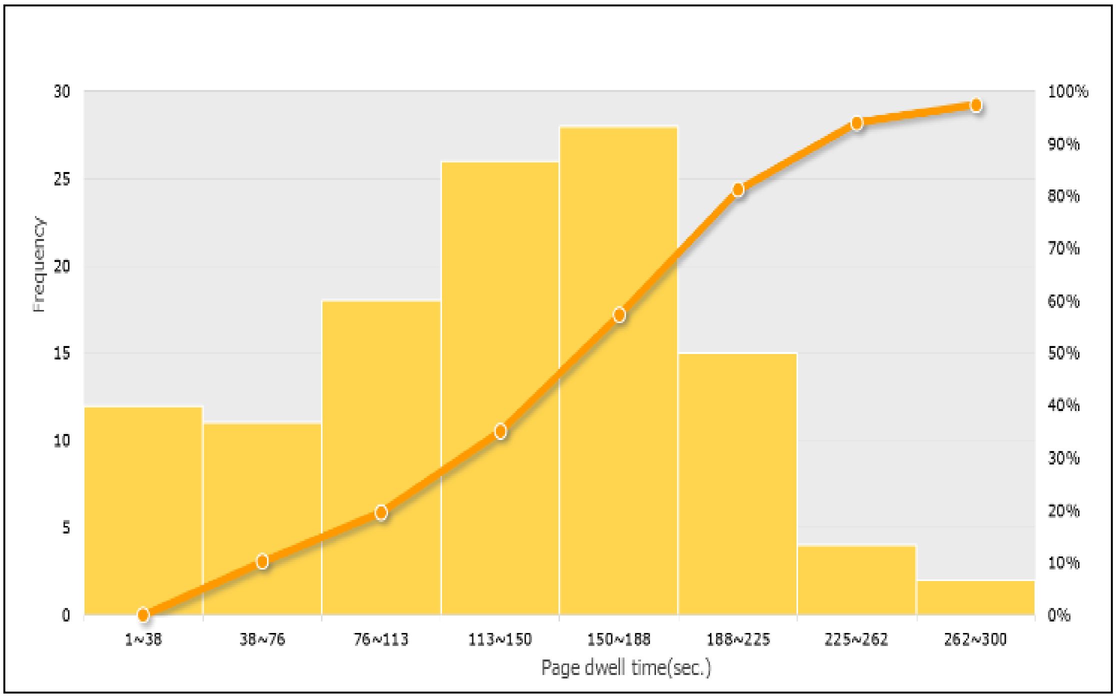


Figure 35. Web Magazine: Frequency Distribution Chart

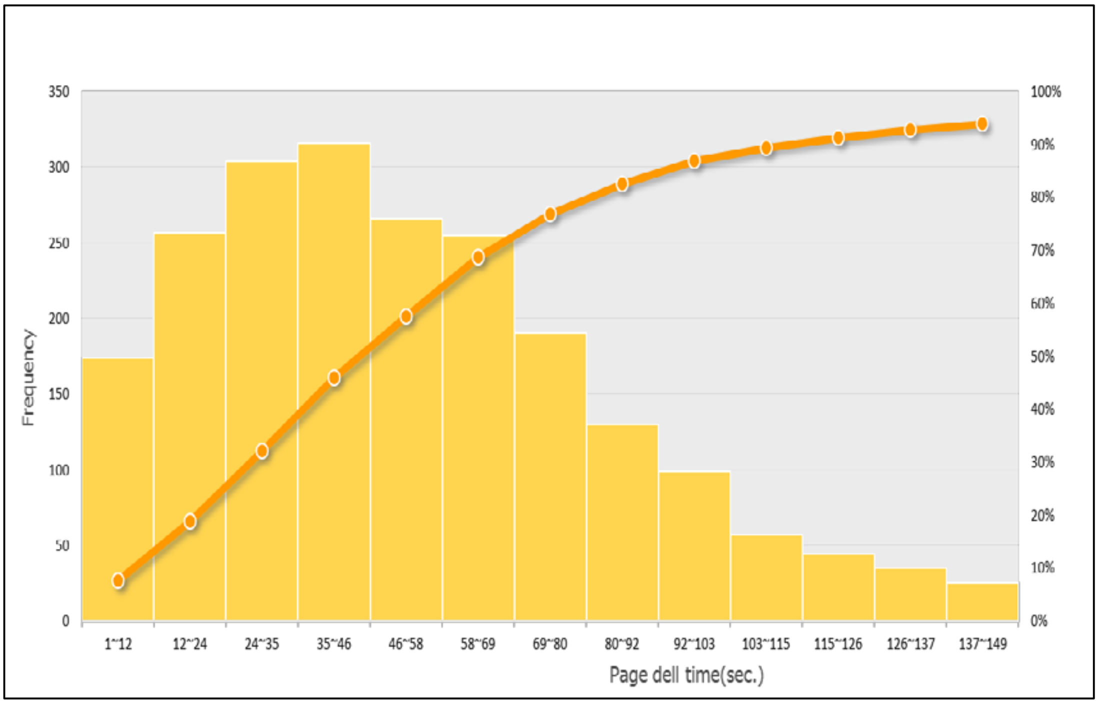


Figure 36. Product Spec: Page Distribution Chart

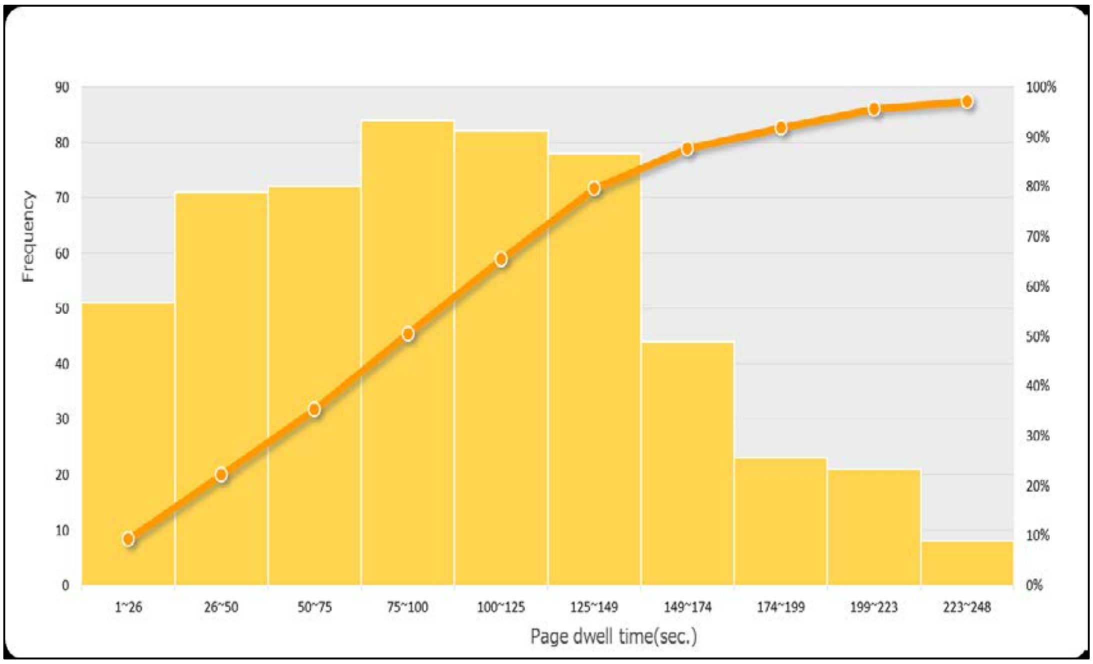


Figure 37. Press Release: Page Distribution Chart

4.3. Tracking participation for conversion

“Conversion” means the achievement of a user’s final goal in web activity. In typical B to B markets, the conversion target of a website is not necessarily a purchase, unlike in Business to Consumer markets. Objects download for program source, document download, and sales inquiry can be conversions sometimes. User registration especially is the most common conversion for websites. We did many surveys on which metric is more related to conversion participation and we did not find a strong relationship between page dwell time and conversion participation, as shown in Figure 38.

However, we see there is most likely a direct proportion between page views and participation.

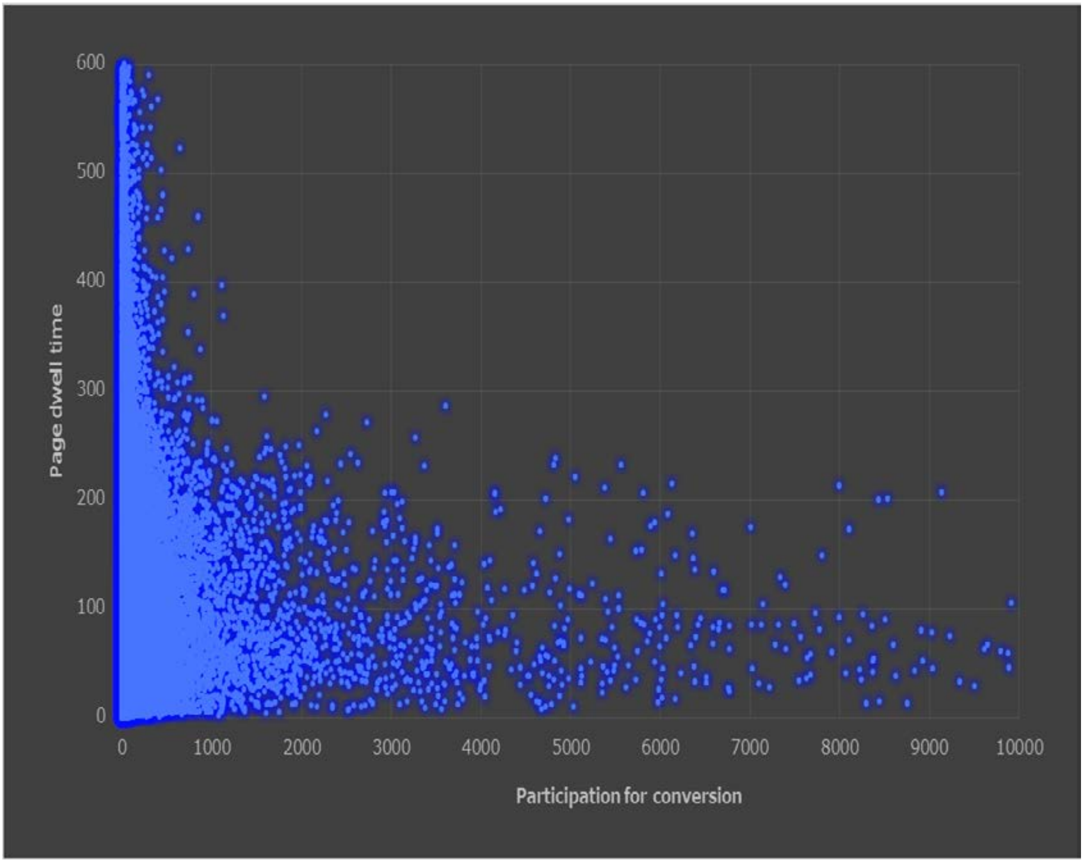


Figure 38. Typical Page Dwell Time

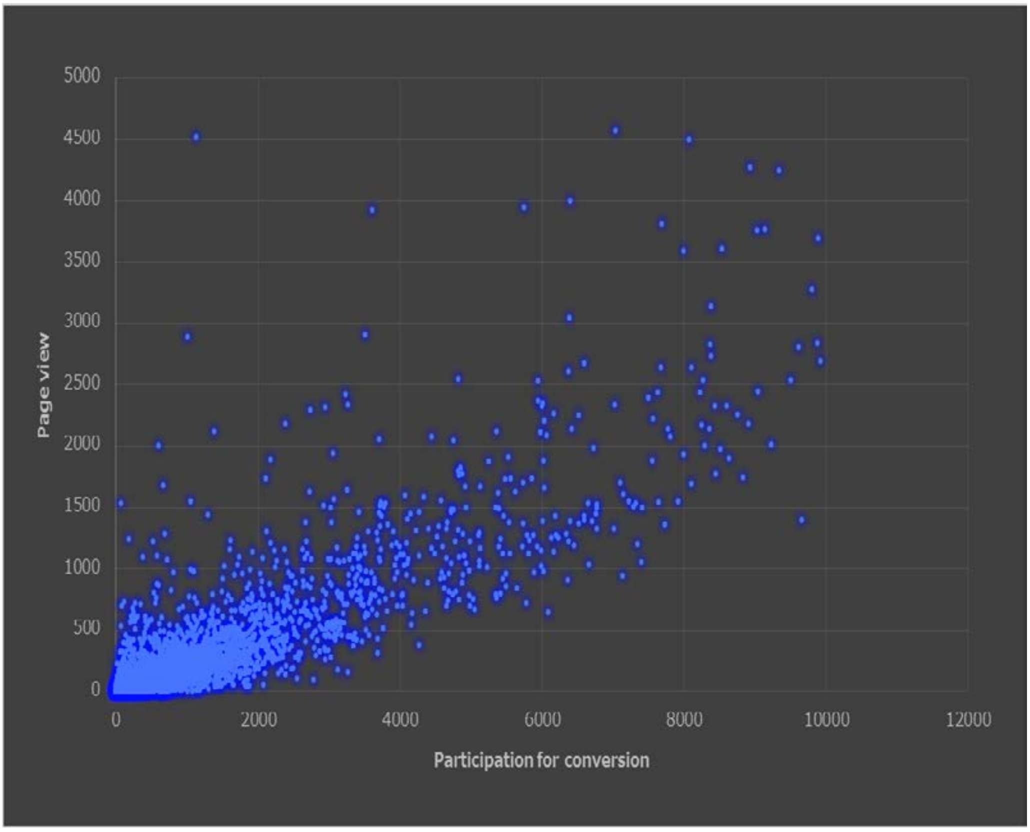


Figure 39. Product Spec Participation Dwell Time

4.4. Segment by Registered and Unregistered Users

As we stated earlier in this report user registration is one of the key conversions in a B to B web site and manufacturers can consider the following concerning user registration. Manufacturers need to urge visitors to register with several promotions. Once they are registered, the manufacturer can get contact information and a highly qualified customer list. Web behavior can differ completely between registered and unregistered users. Need to define the differences and use the results to create a web usability strategy optimizing each segment.

Table 8 shows the differences in bounce rate. "Bounce rate" means the rate of visits in which a user comes to a page but exits the site immediately. In this table, the bounce rate of generally unregistered users is relatively higher than that of registered. In particular, the homepage is normally a frequent entry page but the bounce rate is high for unregistered users. Registered customers continue seeking information more often than unregistered users.

Table 8. Bounce Rate by Registered Users and Unregistered Users

Pages	Registered users			Unregistered users			Unregistered-Registered bounce rate difference
	Visit (%)	Visit (%)	Bounce rate (%)	Visit (%)	Visit (%)	Bounce rate(%)	
Total	16,823	100	20.09	104,720	100	48.69	-29
Home	6,718	39.93	12.23	27,201	25.97	25.63	-13
PartNo Search:SearchResults	2,799	16.64	13.83	9,041	8.63	19.63	-6
Login-Case1	2,082	12.38	0.00	2,988	2.85	0.00	0
KeywordSearch: SearchResults	1,264	7.51	16.67	2,638	2.52	17.50	-1
Disclaimer	1,088	6.47	33.33	882	0.84	31.91	1
Login-Case2	949	5.64	0.00	83	0.08	0.00	0
A Product	928	5.52	8.22	2,032	1.94	20.63	-12
B Product	921	5.47	12.50	1,697	1.62	26.20	-14
Supporting tool category	863	5.13	10.81	1,400	1.34	28.23	-17
Product category	709	4.21	4.42	2,929	2.80	13.50	-9
C Product	664	3.95	12.86	3,024	2.89	21.71	-9

Pages	Registered users			Unregistered users			Unregistered-Registered bounce rate difference
	Visit (%)	Visit (%)	Bounce rate (%)	Visit (%)	Visit (%)	Bounce rate(%)	
Supporting tool A	581	3.45	16.08	995	0.95	31.91	-16
C Product	560	3.33	18.18	770	0.74	27.87	-10
Press release一	454	2.70	47.83	7,999	7.64	78.12	-30
Supporting tool B	429	2.55	8.70	634	0.61	29.09	-20
D Product	406	2.41	10.00	992	0.95	23.00	-13
E Product	400	2.38	13.64	1,582	1.51	27.24	-14
Supporting tool C	396	2.35	11.35	1,070	1.02	33.71	-22
F Product	394	2.34	16.67	430	0.41	30.00	-13

Table 9 shows how users reach the site. Using referrer logs in the http protocol we can see what percentage are coming from search engines, e-mail blast, and so on. As we expected, more unregistered users come to the site via a search engine than registered users.

Table 9. Data on How Users Reach the Site

Referrer type	Registered users		Unregistered users		Unregistered - Registered reach through rate difference
	How do users reach the site? (Reach through number)	How do users reach the site? (Reach through %)	How do users reach the site? (Reach through number)	How do users reach the site? (Reach through %)	
Total	20,711	100.00%	137,960	100.00%	100.00%
Search Engines	9,518	45.96%	91,783	66.53%	70.16%
e-mail	6,124	29.57%	26,382	19.12%	17.28%
Other Web sites	4,996	24.12%	19,004	13.78%	11.95%
Social Networks	73	0.35%	791	0.57%	0.61%

Table 10 shows which pages are exit pages and exit times/total visit times. In this case registered users stay on the site ("stick") longer and for example the homepage isn't a frequent exit page even though unregistered users have a high rate of exiting from the homepage.

Table 10. Exit Frequency in Pages (Top 10)

Item	Registered users			Unregistered users			Registered - Unregistered difference (%)
	Exit times from this page	Visit times	Exit times/ Visit times (%)	Exit times from this page	Visit times	Exit times/ Visit times (%)	
Total	16,673	16,806	99.21	101,509	103,088	98.47	1%
Home	1,230	6,715	18.32	9,691	27,077	35.79	-17%
Disclaimer	671	1,088	61.67	612	880	69.55	-8%

Item	Registered users			Unregistered users			Registered - Unregistered difference (%)
	Exit times from this page	Visit times	Exit times/ Visit times (%)	Exit times from this page	Visit times	Exit times/ Visit times (%)	
PartNoSearch:SearchResults	638	2,798	22.80	2,545	9,027	28.19	-5%
Login type 1	596	949	62.80	52	82	63.41	-1%
Login type 2	567	2,082	27.23	1,014	2,985	33.97	-7%
KeywordSearch:SearchResults	244	1,264	19.30	511	2,611	19.57	0%
Press center	185	454	40.75	5,836	7,977	73.16	-32%
Gadget	157	263	59.70	793	1,083	73.22	-14%
Supporting tools	105	580	18.10	260	994	26.16	-8%

Table 11 shows duration of site visits by registration segment; In this case, also we can see registered users' "stickiness" to the site. Half of registered users come to the site every day. That is the reason why manufacturers make much effort to urge visitors to register their profiles and keep them updated.

Table 11. Duration of Visits

Duration of visits	Registered user visits	%	Unregistered user visits	%
Total	16,823	100.00	104,720	100.00
Less than 1 day	8,520	50.64	18,753	17.91
Less than 7 days	4,411	26.22	13,809	13.19
More than 7 days	1,905	11.32	13,384	12.78
First Visit	738	4.39	38,720	36.97
More than 30 days	303	1.80	12,069	11.53
Cookies Not Supported	18	0.11	943	0.90

4.5. Segment by User Environment

As a quick reference, for a B to B web site there is much difference in traffic between weekdays and weekends. However, the trends of traffic by time of day show almost the same peaks across all days. I try to see analytics by user environment. Figure 40 shows general trend in web visit number by hours.

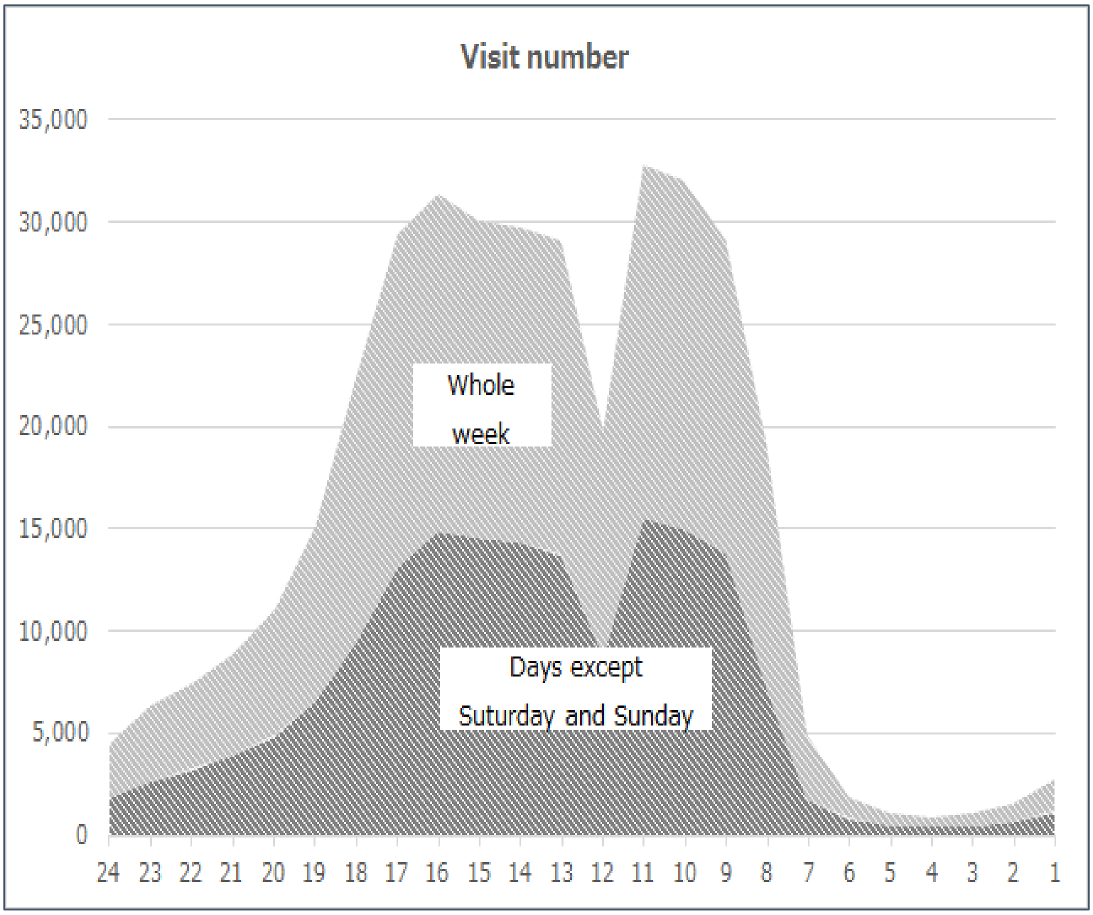


Figure 40. General trend in web visit number by hours

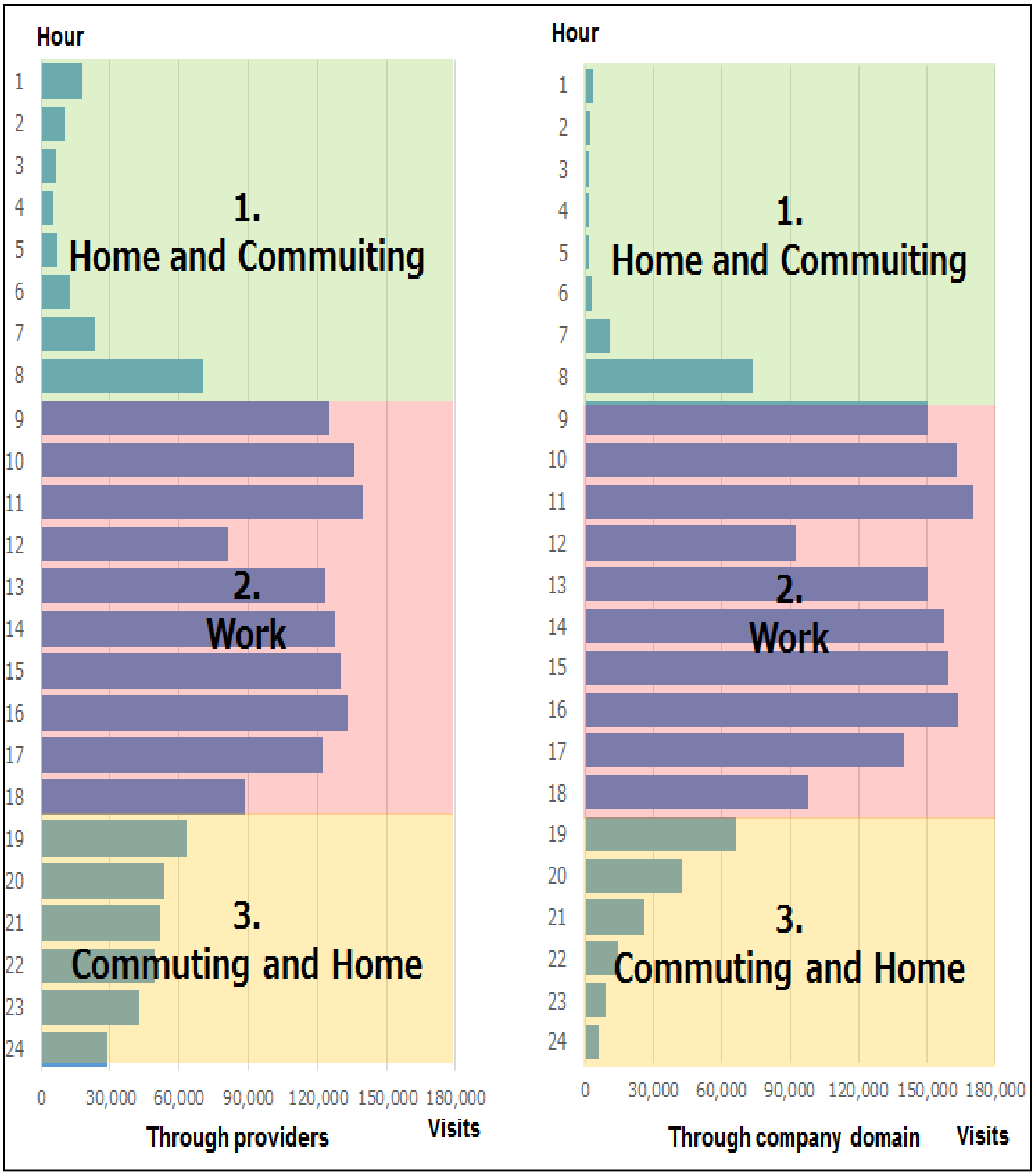


Figure 41. Visit number trend by hours

1) General Trend in Web Visit Number by Hours

According to the statistics provided by the Japan Institute for Labor Policy and Training shown in [107], "hours of work per week, manufacturing" is 42.2 per week. In addition, “9:00 AM to 7:00 PM” are typical working hours in Japan. We defined three times as “1. Home and commuting”, “2. Work”, and “3. Commuting and home”. Firstly, we tracked user accesses by time with consideration to company size. Normally small-sized companies or individual engineers tend to use normal internet providers and middle or large- scale companies use their own domains. We tracked them by time of day distinguishing the users who came through normal domains and users who came through internet providers (called “Providers”). Figure 41 shows a visit numbers trend.

2) Visit Numbers and Page Dwell Time by Time of Day Through Providers and Company Domain

As a result, the total coefficient of correlation of company and provider users is 0.59 and middle level of correlation (Similar trends) but if we omit the times from 1:00 AM to 9:00 AM, there is a strong correlation of 0.78. This means trends are similar throughout the day except for one period. Only the period between 1:00 AM and 9:00 AM shows some difference in numbers between “via providers” and “via company domain”. To illustrate this in more detail, Figure 42 shows visit numbers between 1:00 AM and 9:00 AM by hour. From late night to morning, we assume some engineers work at home or work at small companies that use connections through providers.

This kind of data is useful for deciding which content should be shown or targeted to customers accessing the web site at each time of day. In addition, it can be assumed that provider users are made up of not just customers but also a general audience who are looking for IR information, company information or even some news through the sites. In fact, during this period numbers for these contents are relatively higher than during business hours. The proportion of IR/press release visits are 33% higher compared to normal working hours.

Next, we looked at the page dwell time. The total coefficient of correlation is 0.68 for access via providers and via company domains. However if we calculate the correlation for outside working hours i.e. 7:00 PM to 1:00 AM, the correlation is 0.94.

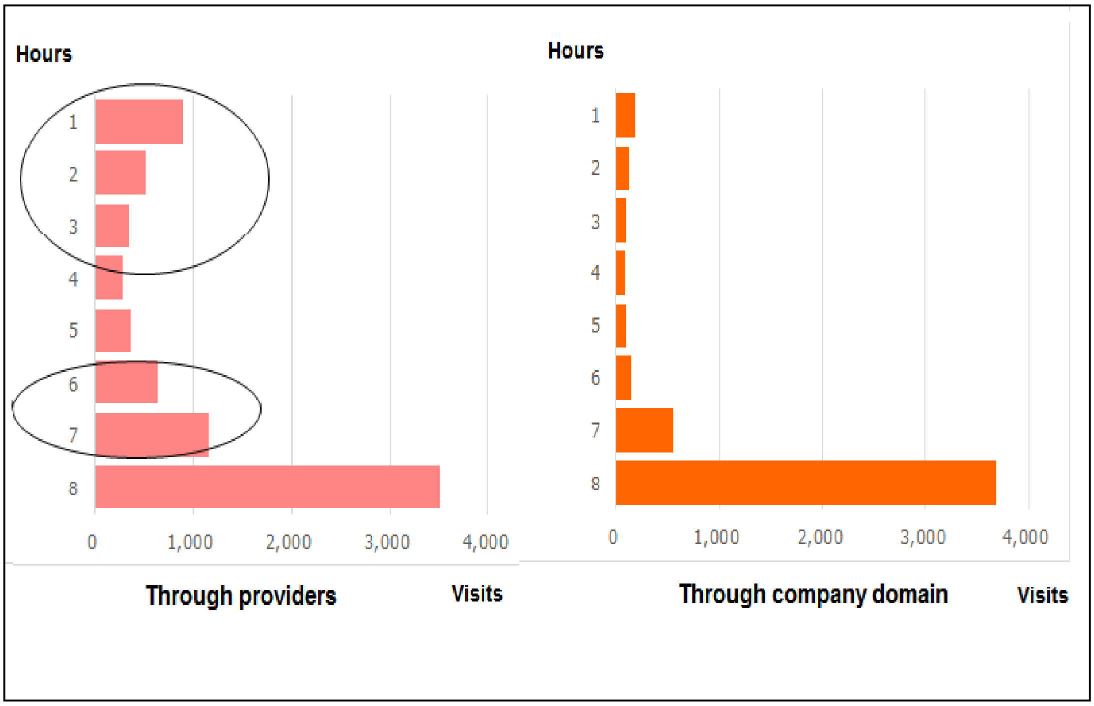


Figure 42.　Visit Numbers from 1:00 AM to 9:00 AM

Next, we looked at the page dwell time. Please refer to Figure 43. This is average of page dwell time by each hour for providers and company domain. The total coefficient of correlation is 0.68 for access via providers and via company domains. However, if we calculate the correlation for outside working hours, i.e. 7:00 PM to 1:00 AM, the correlation is 0.94. We can see some difference between the connection types for these hours. This shows the possibility of differences in usage between provider users and company users. The types of pages that are actually viewed are different. Generally, company users view purchasing information more and provider users view more press releases or IR information.　We will investigate which information is accessed more in our next study.

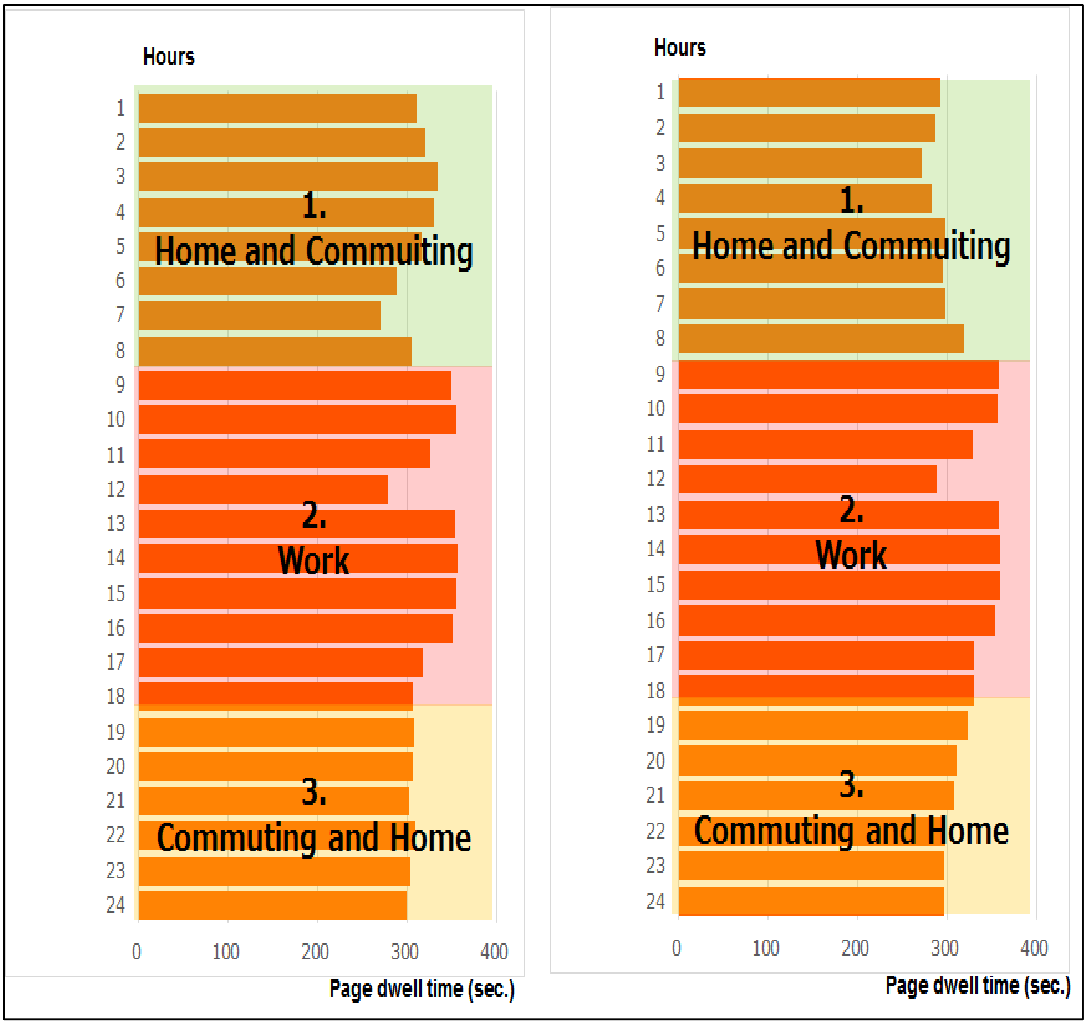


Figure 43. Page Dwell Time by Time of Day through Providers and Company Domain

Please refer to Figure 44 for page dwell time by time of day by connection type. Page dwell time for small-sized customers who use providers peak at 10:00 PM and they probably work from home or on trains while commuting in Japan. This can be related to the fact that trains are the most common way of commuting in Japan. In addition, for company domain users this could indicate engineers working on development overnight.

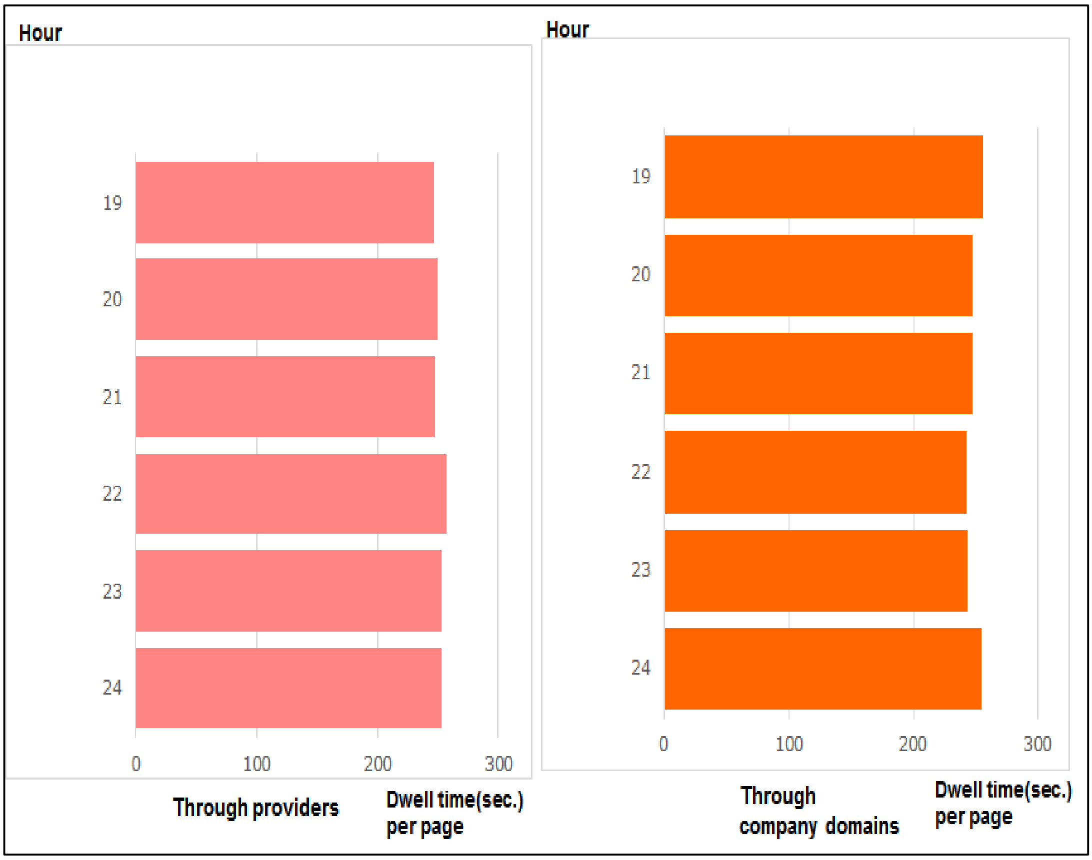


Figure 44. Page Dwell Time by Time of Day through Providers and Company Domain from 7:00 PM to 1:00 AM

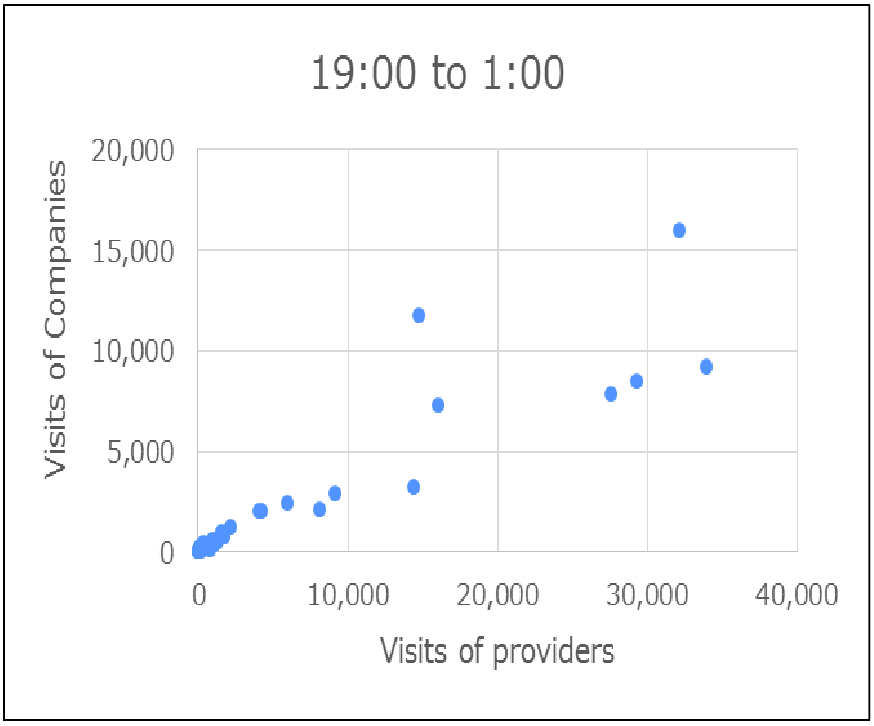


Figure 45. Correlation of visits from 19:00 to 1:00

Page dwell time by time of day through providers and company domain from 7:00 PM to 1:00 AM

Figure 45 shows correlation of visits from 19:00 to 1:00. Visit number is correlated between them and not so much difference.

3) Analysis by Directory

We surveyed the correlation between provider users and company users in terms of several segments. Firstly, we looked at correlation by content category (directory). There is a strong correlation for dwell time between providers and companies shown in table 12. Table 13 shows correlation coefficient in page dwell time for each hour and connection type. However, there is some different correlation just for some directories. Referring to TABLE III, the search function is one area of differentiation, especially in the 1:00 to 9:00 zone. Correlation here is lower than other periods. The number of searches performed by provider users is lower than by company users. It is assumed that normally mobile access is through providers and these users are viewing websites during their train commute and do not search for any solutions or products but do view press releases or events during this time.

Table 12. Dwell Time Correlation Totally

Directory / Dwell Time		1:00 to 9:00 Providers	1:00 to 9:00 Companies	9:00-19:00 Providers	9:00-19:00 Companies	19:00to24:00 Providers	19:00to24:00 Companies
1:00 to 9:00	Providers	1.00					
	Company	0.84	1.00				
9:00-19:00	Providers	0.98	0.83	1.00			
	Company	0.88	0.92	0.88	1.00		
19:00to24:00	Providers	0.92	0.80	0.91	0.87	1.00	
	Company	0.91	0.84	0.90	0.86	0.91	1.00

Actually, the company in this study tries to provide a different user interface to different customers depending on the period. For 19:00 to 1:00, some navigation elements are changed with A/B testing, and the conversion rate for downloads is 125 times higher for time targeting. This type of analysis can be used for marketing purposes. For this purpose, we will keep studying for further details.

Table 13. Correlation by Content Directory

Directory	1:00 to 9:00		9:00 to 18:00		19:00 to 1:00	
	Providers	Company	Providers	Company	Providers	Company
products	106,475	78,981	556,082	595,534	128,806	76,145
Search	21,377	30,217	167,138	193,837	35,397	22,751
support	26,514	19,350	120,251	127,775	32,221	15,962
press	20,321	11,382	89,733	77,086	34,035	9,186
comp	18,817	9,361	89,042	74,004	29,369	8,441
gur	16,049	16,175	84,245	115,158	14,808	11,761
edge_ol	15,972	6,116	64,111	52,709	27,620	7,830
applications	9,994	6,134	48,677	52,147	16,080	7,286
career	7,877	2,579	31,870	20,476	14,428	3,193
ir	6,894	3,747	25,322	21,894	9,203	2,854
disclaimers	4,852	3,736	17,557	17,190	4,247	2,021
company_info	4,164	1,663	18,134	14,629	8,118	2,064
event	4,131	3,638	18,706	22,214	4,125	1,997
partner	3,777	2,322	22,313	19,933	6,018	2,426
contact	2,238	1,821	12,022	11,829	2,163	1,257
public	1,602	1,758	9,243	12,234	1,627	960
buy	1,601	957	6,625	5,950	1,737	757
myrenesas	1,060	990	4,766	6,171	1,209	562
cmn	1,009	632	3,907	3,514	1,175	408
purposes	952	548	3,241	2,672	1,058	326
secret	906	908	6,164	7,962	973	587
videoclip	776	437	3,253	2,966	1,036	387
redirect	750	376	3,515	3,436	1,359	528
chat	640	439	3,580	3,678	613	338
Inquiry	557	495	3,023	3,145	436	371
search	459	564	2,396	3,644	406	433
user	436	133	1,981	829	833	133
edge	424	321	2,022	2,730	812	458
_print_this_page_	389	403	1,669	2,022	310	251
smart	311	171	1,399	1,485	453	173
devcon_jpn_2014	238	204	1,362	1,455	357	147
prod	147	135	959	1,192	196	167
ecology	131	69	461	613	198	103
media	128	182	681	1,413	153	271
facebook	103	41	548	277	187	46
sitemap	93	50	380	339	87	29
legal	88	75	383	461	104	46
tech	84	52	324	401	172	76
guidance	75	84	338	404	53	31
csr	63	20	231	157	115	25
privacy	44	95	212	270	57	18
campaign	34	24	151	137	55	14
lib	33	30	180	192	30	19
registration	32	25	116	139	18	15
rss	29	20	134	176	43	15
tool	29	23	116	220	24	22
C:	18	5	106	50	16	4
supp	15	8	40	86	30	8
r_video	13	9	80	102	30	6
manga	8	1	10	2	10	2

Table 14. Correlation by OS Type

OS Type / Dwell Time		1:00 to 9:00 Providers	1:00 to 9:00 Companies	9:00-19:00 Providers	9:00-19:00 Companies	19:00to1:00 Providers	19:00to1:00 Companies
1:00 to 9:00	Providers	1.00					
	Company	0.28	1.00				
9:00-19:00	Providers	0.97	0.27	1.00			
	Company	0.40	0.89	0.31	1.00		
19:00to1:00	Providers	0.91	0.33	0.91	0.39	1.00	
	Company	-0.03	-0.08	0.09	-0.15	-0.18	1.00

4) Analysis by Device

We also looked at the relationship by device. We cannot see the actual device that a user owns but we can see information on OS (Operating System). There is much less correlation between providers and company trends in the periods “1:00 AM to 9:00 AM” and “7:00 PM to 1:00 PM”. Most likely the mobile device usage rate is higher in non-working hours than working hours as shown in table 14 and table 15. Both table show correlation coefficient in page dwell time for each hour and connection type.

Currently, unlike B to C sites the layout of most B to B sites is not mobile device compliant. However, B to B sites need to think about mobile device compliance especially for users who access through providers.

Table 15. Correlation by OS Type in Details

Item	1:00 to9:00				9:00 to 19:00				19:00 to1:00			
	Provider	%	Company	%	Provider	%	Company	%	ISP	%	Company	%
GNU/Linux	1,662	0.78%	632	0.43%	5,257	0.48%	4,152	0.35%	2,689	0.89%	1,121	0.77%
Microsoft Window:	162,070	75.83%	139,460	95.45%	947,855	85.98%	1,145,688	97.66%	211,999	69.86%	134,006	92.22%
Others	208	0.10%	19	0.01%	358	0.03%	91	0.01%	340	0.11%	46	0.03%
UNIX	38	0.02%	7	0.00%	104	0.01%	76	0.01%	47	0.02%	14	0.01%
Apple Macintosh	5,937	2.78%	1,710	1.17%	20,218	1.83%	9,893	0.84%	12,009	3.96%	3,028	2.08%
Unspecified	63	0.03%	16	0.01%	269	0.02%	96	0.01%	177	0.06%	34	0.02%
Google Android	19,312	9.04%	2,156	1.48%	55,271	5.01%	6,543	0.56%	33,457	11.03%	3,550	2.44%
Apple iOS	24,395	11.41%	2,091	1.43%	72,954	6.62%	6,504	0.55%	42,705	14.07%	3,493	2.40%
Microsoft Window:	24	0.01%	8	0.01%	52	0.00%	32	0.00%	18	0.01%	7	0.00%
Blackberry	7	0.00%	7	0.00%	20	0.00%	12	0.00%	14	0.00%	4	0.00%
Symbian	9	0.00%	3	0.00%	7	0.00%	0	0.00%	4	0.00%	1	0.00%
WebOS	0	0.00%	0	0.00%	1	0.00%	0	0.00%	0	0.00%	0	0.00%
Adobe	0	0.00%	0	0.00%	1	0.00%	1	0.00%	1	0.00%	0	0.00%

Other examples of no correlation are "viewed page numbers" and search usage time shown in table 16 and table 17.

Table 16. Viewed Page Number Correlation

Viewed page numbers		1:00 to 9:00		9:00-19:00		19:00to1:00	
Dwell Time		Providers	Companies	Providers	Companies	Providers	Companies
1:00 to 9:00	Providers	1.00					
	Company	-0.23	1.00				
9:00-19:00	Providers	0.78	-0.33	1.00			
	Company	-0.30	0.48	-0.37	1.00		
19:00to1:00	Providers	0.68	-0.22	0.68	-0.30	1.00	
	Company	-0.17	0.34	-0.24	0.35	-0.14	1.00

Table 17. Correlation with Search Usage Time

req (trend daily) Visit		1:00 to 9:00 Providers	1:00 to 9:00 Companies	9:00-19:00 Providers	9:00-19:00 Companies	19:00to1:00 Providers	19:00to1:00 Companies
1:00 to 9:00	Providers	1.00					
	Company	0.91	1.00				
9:00-19:00	Providers	0.70	0.87	1.00			
	Company	0.65	0.88	0.96	1.00		
19:00to24:00	Providers	0.44	0.52	0.76	0.61	1.00	
	Company	0.54	0.79	0.92	0.94	0.70	1.00

There is much difference between time and connection type and there is possibility navigation can be further optimized according to time of day or connection type.

5) Summary of Findings

We found the user behavior tracking like visit numbers or page dwell time categorized by user segmentation is effective. Especially the accesses like time and place (or connection type) have different trend by each segments. For example, the period between 1:00 AM and 9:00 AM shows some level of difference in numbers between “via providers” and “via company domain”. In addition, for page dwell time 7:00 PM to 1:00 AM period has differentiations between providers and companies. In addition, depending on content type we found some difference. For example, in the 1:00 to 9:00 zone, user behavior is different and the number of searches performed by provider users is lower than by company users. It is assumed that normally mobile access is through providers and these users are viewing websites during their train commute and do not search for any solutions or products but do view press releases or events during this time. We also looked at the relationship by device. I found that mobile device usage rate is higher in non-working hours than working hours and viewed pages are different between them.

4.6. Chapter Summary

I proposed segmentation model for B to B analytics, like information driven, user environment driven, user behavior driven, and business relationship driven.

"User environment driven" has two elements as "By time and place" and "By Device type". "User behavior driven" is comprised of "By user referrer"," By visit frequency", and "By user commitment level". "Business relationship driven" has two elements as "By company profiles" and "By industry". I tried each related studies and you can see them in related sections in this report. I confirmed segment by content and segment by user environment especially in this chapter.

For B to B sites, we have several personas (use case by segment) and web analytics need to be done by segment. We defined some of the segment models and examined web access using some segments. One of the most important segmentations is registered users versus unregistered users. User behavior is very different with each use case. Bounce rate, referrer (how they reach the site), and exit page analysis especially are beneficial and we can see that registered customers' stickiness to the site/company is much stronger than that of unregistered users. This can be measured by some metrics by segment, like duration of visit.

I surveyed correlation of access by user environment. There are correlations between time of day or correlation between connection types such as connecting through a provider or through a company network. I used some key web metrics such as visits and page dwell time for our correlation survey. I noticed user environment segments with a correlation approach can be used for web analytics for user navigation studies or even marketing use.

5. Effective User Registration Procedure and Improvement Method

5.1. Background and Purpose of This Chapter

On B to B manufacturer web site, web user registration form is used to register web visitors' information. It acts as a critical user entry point for B to B manufacturing firm that places more emphasis on on-line marketing. For instance, B to B web registration form could ask web visitors' personal information such as first name, family name, e-mail address and occupational information including company name, department name and so on. It also asks visitors' interest about services including topic preference for e-mail newsletter subscription.

Web registration form on B to B site often works as a gate for privileged on-line and off-line services. In fact, we see that B to B form asks visitors' information for granting access to: whitepaper and technical documentation downloads, customer support such as inquiry and on-line chat, as well as off-line tradeshows and business seminars. Those visitors who have registered in web form are sometimes considered more valuable to manufacturing firm than non-registered visitors because they had taken extra time to fill in registration form and subscribed to the firm's service as well as the firm could initiate marketing action such as sending promotional e-mail based on the registered information. Then, noting the importance of the form, manufacturing firm has been trying to improve usability of the web registration form such that it could increase number of user registration through the form, in other words increase in the form conversion rates.

In this section, I analyzed three sets of web registration data and conversion rates. Those sets of data are relevant to three different versions of web registration form. Each set of data contains two and half months' term of web access data from one manufacturer web site. In addition, I introduce relevant and underlying works. I analyzed a situation for manufacturer web registration form and argue that its exit rate poses a space for improvement. I illustrated and explained two types of manufacturer web registration forms created as a result of improvement. Finally, I analyzed exit rate of the web registration forms in detail.

5.2. Initial Situation and Analysis of Web Form

In this section, I introduce web registration form of a manufacturer site and analyze situation. In our previous studies, I came up with a web analytics scheme for B to B websites and defined B to B site conversion type and importance of user registration on web site in the reference [4]. In another study, I found that there was behavioral difference between registered and unregistered users. Registered users tended to stay on manufacturer web site longer and visit more frequently than non-registered users. Thus, I concluded that this type of registered users' "stickiness" to the manufacturer web site made registered users' segment more appealing to manufacturer for marketing actions in the reference [3].

Web registration form is typically used on B to B manufacturer web site to collect information of registered users. In figure 46, it shows web registration form for a manufacturer site. It asks users for personal information such as first name and family name, e-mail address. It also asks for occupational information including company name, department name, mailing addresses. The form allows users for setting up ID and password for login.

I have gathered web form registration data for the manufacturer in two and half months' term in 2009. Results are shown in figure 47 There were about 37% of users successfully registered or converted on the form while rest of the users were either exiting the form page without filling in any field or exiting the page after filling in at least one field on the page. In other words, the manufacturer had 63% of exit rate. Former type of users was amounted for 42% and latter type of users was 21% of total users on the form. These results told us that most of the users were exiting the registration form page without filling in any field on the form.

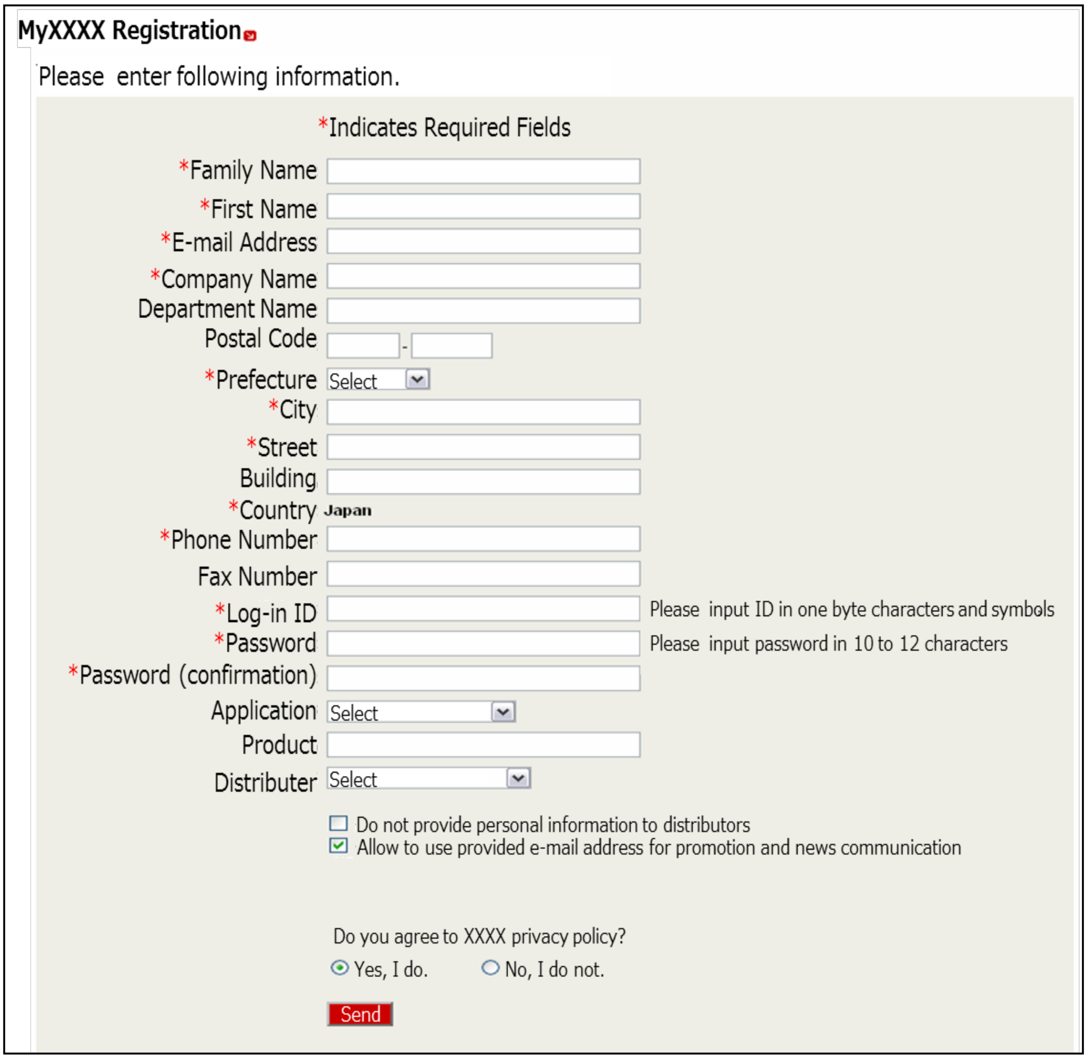
Following the overall analysis of the form, I have studied exit rate as well as error rate of each field on the registration form in detail. Results are shown in figure 48. From the total number of users who have filled in at least one field on the form, I observed that 23.9% of exit was happening at the name of sales distributor field, 13.1% of exit was at the first name field and 11.3% of exit was at the family name field. In addition, there were 53.9% error rate at the password field. Although there are many ways to cause error on the registration form, for instance, a user could forget to fill in a required field, more than half of error was happening at the password field.

Given these figures, we could say that lots of user were having difficulty in completing the registration form and resulting in the above 63% of exit rate as a whole.

Initially, there was no special consideration about improving the web registration at the manufacturer because B to B users are thought to be more purpose driven than B to C users who are emotional. Following their business purpose such as obtaining technical documentation from the manufacturer site, B to B users are more willing to fill in registration form. However, given the fact that many users are exiting and not even filling in any field on the form, the firm started to think about the cause of the exit rate result.

One possible case was that the registration form asked too much to the users. The form had 22 input fields of which 12 fields are required to fill in. This number of input fields could be acceptable for certain users, namely existing customer of the manufacturer who was looking for technical support documentation working on product. However, this might not be the case for prospective customers who were just taking a look at the firm's product or comparing firm's offering to competitors. If this case held true, the firm was losing prospective customers on its web registration form. Then, the firm came to conclude that it needs classification for users.

To be more precise, the firm classified users into two types. One type is "loyal customer" who is actively and positively looking for the firm's offering in detail. Second type is "prospective customer" who is skimming through firm's offerings. Based on these classifications, the firm introduced stepwise registration procedure that allows prospective customer to input minimal information such as email address at first. Then, the customer is being asked for more information including name of sales distributors. This stepwise registration procedure avoids asking too much information in front and helps prospective customers gradually introduced to the firm's offering while they are being asked for more information without intimidation.



MyXXXX Registration

Please enter following information.

*Indicates Required Fields

*Family Name

*First Name

*E-mail Address

*Company Name

Department Name

Postal Code -

*Prefecture Select

*City

*Street

Building

*Country Japan

*Phone Number

Fax Number

*Log-in ID Please input ID in one byte characters and symbols

*Password Please input password in 10 to 12 characters

*Password (confirmation)

Application Select

Product

Distributer Select

☐ Do not provide personal information to distributors

☑ Allow to use provided e-mail address for promotion and news communication

Do you agree to XXXX privacy policy?

◉ Yes, I do. ○ No, I do not.

Send

Figure 46. First Version Web Form

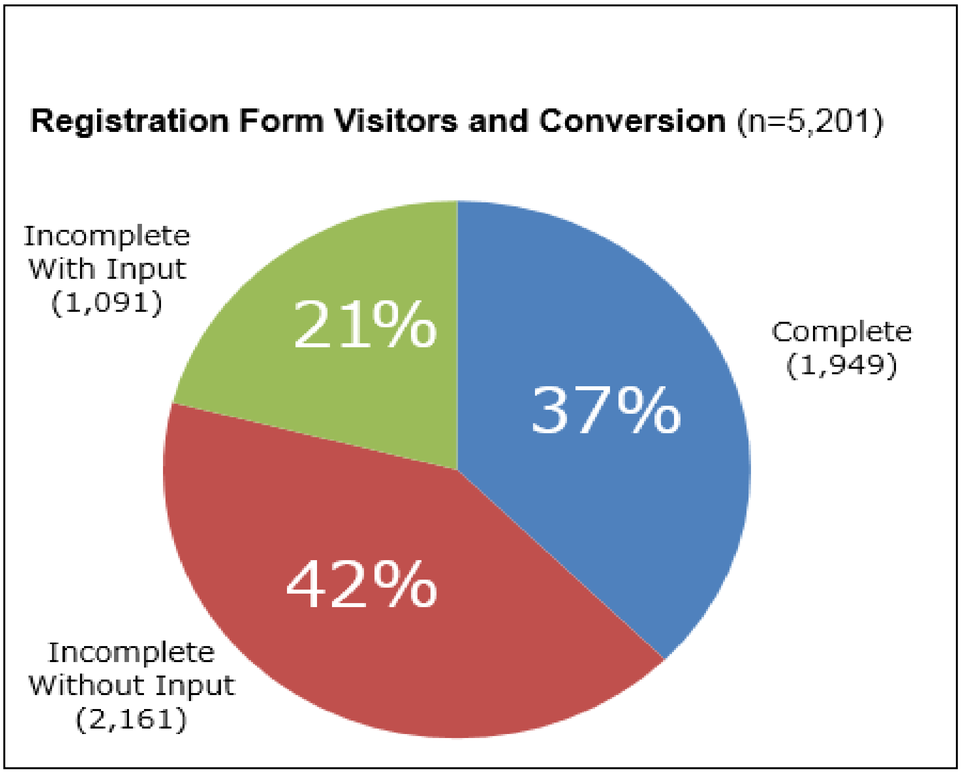


Figure 47. Conversion Proportions

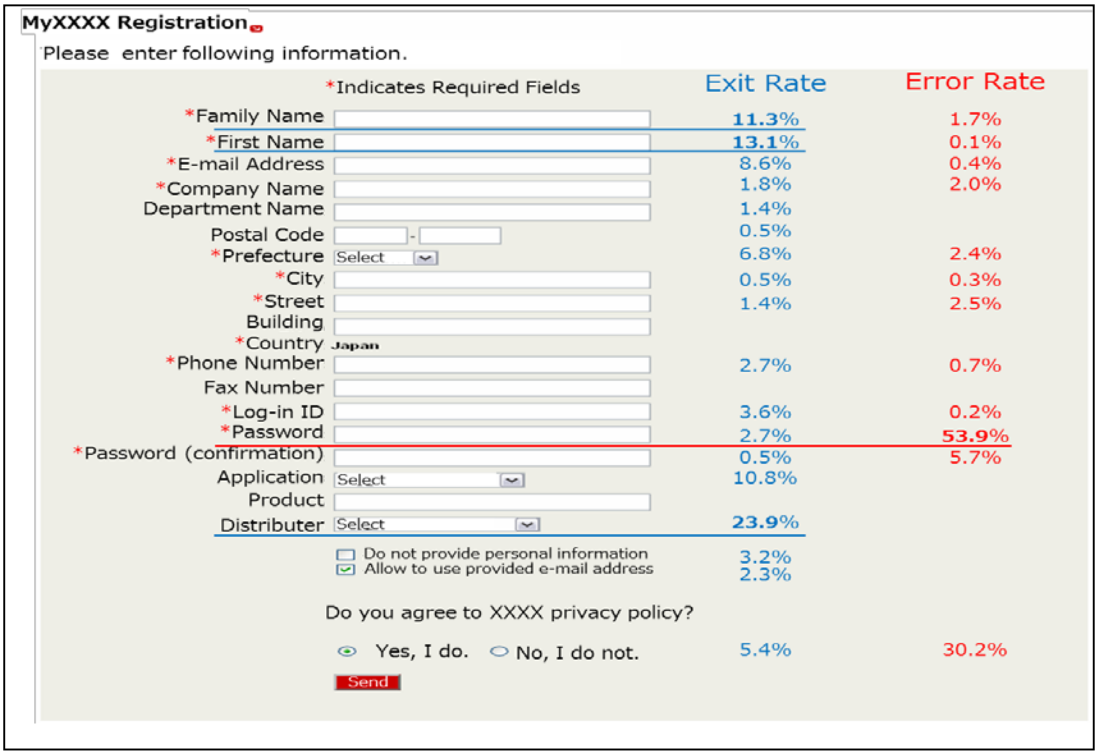


Figure 48. Exit and Error Rates by Fields

5.3. Assessment and Analysis of Modified Web Form

In this section, I investigate change in user registration after the manufacturer introduced different types of web registration form. Given the analysis of the previous section, the manufacturing firm has created multiple stepping user registration forms.

I have studied the manufacturer's web registration process starting from the entry of e-mail address to the point of completion where registered user is able to log in his/her account and tried to see difference in web page visitors and relevant conversion rates. Conversion rates are given by number of web page visitors on a subsequent page divided by number of web page visitors on a previous page in the manufacturer's web registration process. Then, the difference in visitors and conversion rates are analyzed from its context and content perspectives. From the context viewpoint, total number of registration steps, number of input fields, number of required input fields and timing of which those input fields are presented are analyzed. Type of information being asked at a given process step is analyzed as a difference in content.

In figure 49, I illustrate three different types of user registration process that the manufacturing firm has had on its web site for past 5 years. Given the analysis of previous section, the manufacturer successively introduced different registration processes and web forms.

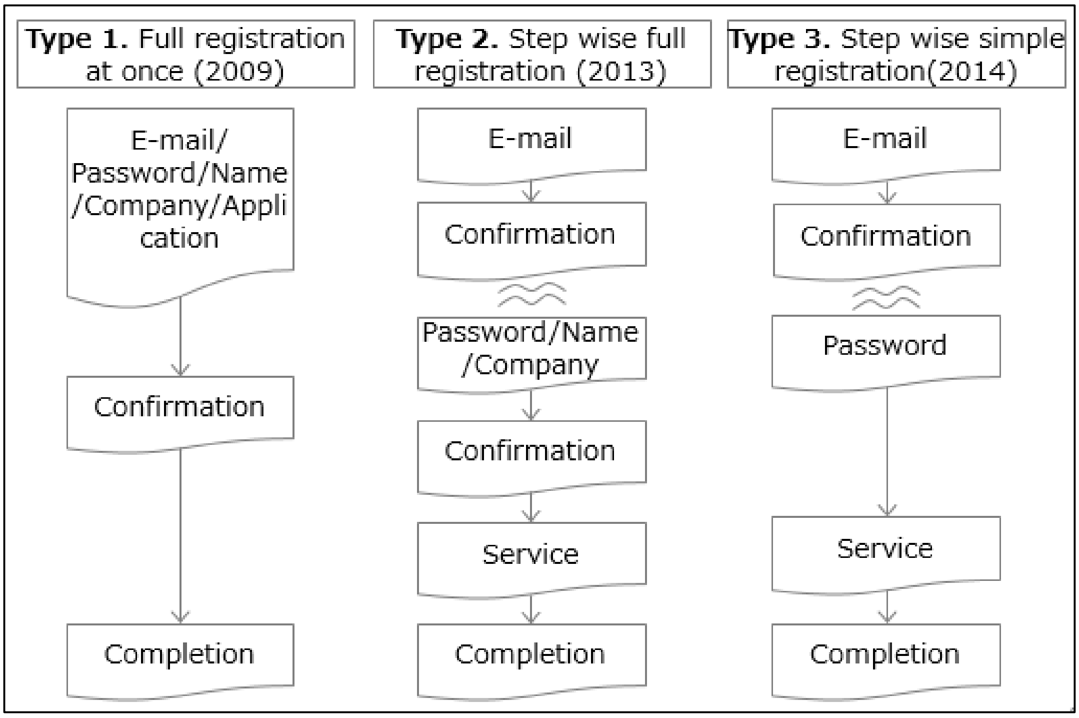


Figure 49. Types of Registration Process

First type is named "Full registration at once". This Type 1 registration process is what we have seen in the previous section as the manufacturer's initial situation in 2009. There were 3 steps in the registration process. In its first step, a single registration form asks information including e-mail address, password, first name, family name, company name and preferred application. Then, the process shows confirmation page as a second step where web form visitor confirms information entered in the first step. At last, the visitor sees registration completion page where it tells visitor that he/she has successfully registered.

Second type is "Stepwise full registration" form that was introduced in 2013. This type of form features in its stepwise process. As an initial step, the form asks visitor for his/her e-mail address. As I have mentioned earlier, e-mail address is considered an important information for the manufacturer because it allows for further communication to the visitor. After entering an email address on a form, visitor is told that temporal registration has been completed on next web page. Then, the page asks visitor to check his/her email account corresponding to the email address entered in the previous form page.

When the visitor opens email account, he/she finds an email from the manufacturer. Furthermore, the visitor is asked to click an URL to come back to manufacturer site in order to complete registration procedure. This procedure for sending email to entered email address and reconfirming visitor's intention for registration is called double opt-in. In this figure, I take these procedures from the temporal registration completion to the URL click as a single "Confirmation" step in order to simplify our argument. When visitor is returning to the manufacturer site, as a third step, another form asks visitor for setting password, providing name, company name etc., as it was the case for the Type 1 registration process. At its fourth step, visitor is asked to confirm entered information in the previous step. Then, the visitor proceeds to service preference registration form page as next step. This form asks visitor to specify product type such as microcomputer, analog device, and system-on-chip. The form also asks visitor if he/she prefers to receive information from the manufacturer including email newsletter and seminar information.

Finally, the visitor reaches to registration completion page similar to Type 1 above.

Last type of the manufacturer's registration form is named "Step wise simple registration". This type represents the latest registration form on the manufacturer's web site that was launched in 2014. Type 3 registration form features not only in stepwise process but also in simplified and prioritized questions of the form. Purpose of Type 3 registration process is to gather minimal amount of information from visitors such as email address and service preference. Then, through its marketing communication, the firm collects rest of visitors' information such as company name. First couple of steps is similar to what we have seen in Type 2 above. The registration form asks visitor's e-mail address. Then, through its double opt-in registration procedure, visitor is asked to confirm his/her intention for registration. Once, visitor comes back to the manufacturer's web site by clicking URL embedded in an e-mail, he/she is asked to set password. This is where we see difference in registration process between the Type 2 above and Type 3. As I recall Type 2, the form asked visitor to entre more information. After setting password, the visitor is directed to another form where he/she is asked for service preference. Then, the visitor is introduced to registration completion page similar to the other types. Comparing to Type 2 registration process, confirmation page after the password entry page has been omitted due to less amount of information being entered in Type 3. In other words, the manufacturer made decision not to have the confirmation page in Type 3 registration process since there were only password entry and password confirmation field already built-in the previous page. Given these types of registration forms, I would like to investigate further their difference in number of visitors and conversion rates below.

In table 18, we have comparison of the registration forms. Each type of registration forms is depicted by step description, visitor, total conversion, step conversion, input fields and required fields. Step description column gives overview of each registration steps in terms of the type of information. Visitor column counts number of web page loads as a figure for web page visitors. Total conversion column shows proportion of visitors who get to certain step of registration process. This is given by number of visitors at a registration step divided by number of visitors at an initial registration step. Step conversion column shows proportion of visitors who get to certain step of registration process from immediately preceding step. This conversion rate is calculated by number of visitors at a registration step divided by number of visitors at an immediately preceding step. Input fields show number of items on web registration form. Required fields count for number of fields that causes error without visitors' fill-in. I have studied about 25,000 web site visitors' record in three different periods along with the manufacturer's registration form change. Data acquisition periods are the followings: August to November (2009), November to January (2013) and November to January (2015). Detail of data acquisition is described in table 19. From these data, I would like to give overall observation and analysis of the forms.

Table 18. Number of Visitors and Conversions Fields

	Type 1. Full registration at once (2009)						Type 2. Step wise full registration (2013)						Type 3. Step wise simple registration(2014)					
Step	Step Description	Visitor	Total Conversion	Step Conversion	Input Fields	Required Fields	Step Description	Visitor	Total Conversion	Step Conversion	Input Fields	Required Fields	Step Description	Visitor	Total Conversion	Step Conversion	Input Fields	Required Fields
1	E-mail/password/personal/occupational information registration	5,201	-	-	22	12	E-mail registration	3,256	-	-	4	4	E-mail registration	3,351	-	-	5	5
2	-	-	-	-	-	-	Temporary completion	2,673	82.1%	82.1%	0	0	Temporary completion	2,320	69.2%	69.2%	0	0
3	-	-	-	-	-	-	Password/personal/occupational information registration	1,808	55.5%	67.6%	24	15	Password registration	1,860	55.5%	80.2%	2	2
4	Input confirmation	1,949	37.5%	37.5%	0	0	Input confirmation	1,650	50.7%	91.3%	0	0	-	-	-	-	-	-
5	-	-	-	-	-	-	Service information registration	1,509	46.3%	91.5%	6	0	Service information registration	1,755	52.4%	94.4%	2	2
6	Completion	1,021	19.6%	52.4%	0	0	Completion	987	30.3%	65.4%	0	0	Completion	1,664	49.7%	94.8%	0	0

Table 19. Data Description

	Type 1. Full registration at once (2009)	Type 2. Step wise full registration (2013)	Type 3. Step wise simple registration(2014)
Period	2009/8/1 -2009/11/11	2013/11/1-2014/1/15	2014/11/1-2015/1/15
Number of Visitor Records Studied	2,237	11,833	10,950

In table 18, we have comparison of Type 1 and Type 2 of the manufacturer's registration form. At the last registration step, total conversion rate of Type 1 form and Type 2 is 19.6% and 30.3% respectively. The manufacturer modified its registration form based on what I have found in the previous section. As it turns out, the modification improved registration conversion rate. I believe that contextual difference has made Type 2 form convert more visitors than Type 1 form. Type of information being asked on Type 2 form is similar to Type 1 form. Both forms ask visitors' e-mail, password, personal information as well as occupational information. However, timing of asking such information is different. As I recall, Type 1 asked all information on the first step while Type 2 asked password, personal information and occupational information on the third step. I observed that this stepwise registration process that separates registration process and gathers visitors' information gradually is more effective. At their fourth step of the process, Type 2 has 50.7% of total conversion rate while Type 1 has 37.5%.

In table 18, we have comparison of Type 2 and Type 3 of the manufacturer's registration form. If we take a look at sixth step, Type 2 and Type 3 have 30.3% and 49.7% of total conversion rate respectively. It seems more visitors are willing to register on the firm's Type 3 registration form than Type 2. An increase in total conversion rate from Type 2 to Type 3 can be explained by the followings: total number of registration steps, total number of input fields, and type of information being asked. Total number of registration steps is decreased from Type 2 six steps to Type 3 five steps. Total number of input fields is decreased from Type 2 thirty four fields to Type 3 nine fields. In terms of required fields, total number is also decreased from Type 2 nineteen fields to Type 3 nine fields. The decreased total number of registration steps, input fields and required fields would mean less time for visitors to complete the manufacturer’s registration procedure. In other words, shortened time to register produced less chance for visitors getting disturbed while they are working on registration process. Therefore, Type 3 brought more visitors at the end. Moreover, Type of information being asked is different. In Type 2 registration procedure, it asked personal and occupational information at the third step of registration. Some visitors could compare importance of their personal and occupational information against the manufacturer’s expected service for registered users. Then, they could exit the Type 2 registration procedure because their information weighted more than the expected firm’s service offering. Therefore, I believe that decreased total numbers of registration steps, input fields as well as type of information are helping visitors to sign up more in Type 3 than in Type 2 registration process.

We have taken a look at service difference by registration process. When we look at the Type 3 process from the service provisioning perspective, we notice that the Type 3 has two distinctive processes; e-mail registration process that ranges from the first to third step as well as full registration process that is the last two steps of the Type 3 registration. E-mail registration gives user an access to the manufacturer’s newsletter that carries promotional and support information about the manufacturer’s product. In addition, the full registration gives user an access to document download service as well as a personalized newsletter that delivers promotional and support information tailored to user’s preference.

When there are such two steps as e-mail registration and full registration, there are users who registered only for e-mail. Within the only e-mail registered users, there may be users who are satisfied with the services such that stop proceeding to full registration.

In addition, there may be users who are tired of registering further information so that stop proceeding to full registration. When we assume the former type of satisfied users are visiting the manufacturers web site at least twice with their “only e-mail registration” account, there are 24 visitors (less than 1% of initial Type 3 visitor of 3,351). Further, when we assume the latter type of tired users are visiting the manufacturer’s full registration page with their “only e-mail registration” account without full registration, there are 64 visitors (about 2% of initial Type 3 visitor of 3,351). In next paragraphs, I would like to investigate Type 3 further. It is the latest registration forms and its process in detail.

In table 18, Type 3 registration has 3,351 visitors for its initial e-mail registration step and 2,320 for temporary completion, which give 69.2% of conversion rates (i.e. for total and step conversion rates since initial rates are same for both metrics). Although it has similar steps, Type 2 has 82.1% conversion rates from its 3,256 visitors for e-mail registration and 2,673 visitors for temporary registration.

On the e-mail registration page, Type 3 has five input fields all of which are required fields. On the other hand, Type 2 has four input fields, which are also required fields. Thus, as it was the case for entire registration process, having another field on the e-mail registration page could cause lower conversion rate for Type 3.

Taking closer look at the e-mail registration, we have side-by-side comparison of Type 3 and Type 2 registration step in figure 50. I notice that there are two major differences in between the Type 3 and Type 2 e-mail registration form. First, I note that there is an additional input field, namely a privacy and website policy agreement field, on the Type 3 e-mail registration form. This field asks visitor to accept the manufacturer’s policy by filling in a check box field. I tend to think this field hinders visitors from moving to next page.

There is rise in privacy concern in Japan due to large companies’ misconduct or mismanagement of personal information shown in reference [53]. Although it is legitimate to place a policy field for asking visitors’ consent, this additional field may remind them of personal information mistreatment. In addition, the policy field has two web page links. One is a link to external website policy page and the other is another external link to privacy policy of the manufacturer. These external links are supposed to let visitors confirm policy in detail. However, these links open different web pages with policy statements taking visitors time to read through. If there is more time for completing a registration step, then there is also chance for visitors to get distracted and to walk away. In other words, those external links could take visitors away from the registration step. In sum, an additional privacy and website policy field with external links caused lower conversion rate for Type 3.

Figure 50. E-mail Registration Step

Moving to the next step of Type 3 registration where we see a gap from Type 2, in table 18, Type 3 registration has 2,320 visitors for its second temporary completion step and 1,860 for password registration that give 80.2% of step conversion rate. Comparing with its counterpart, Type 2 has 2,673 visitors for the second step and 1,808 visitors for password and other information registration step with 67.6% of step conversion rate. As we recall, this registration step is where we see double opt-in procedure. Visitors are directed to their email account to open and click upon an e-mail from the manufacturer.

Therefore, I tend to look at the temporary completion web page as well as e-mail content in figure 51 in order to fully investigate possible causation of the conversion rate gap. In figure 51, though “Close” button in Type 3 is coloured in grey while the Type 2 button is coloured in red, temporary completion pages do not show much difference in such a way that Type 3 has higher step conversion rate than Type 2.

I note differences when we have closer look at e-mails in Type 2 and Type 3 in figure 52. First, we see that number of embedded hyperlinks is decreased from Type 2 four to Type 3 three. As we have seen in the above, external links could drag visitors away from registration steps. Furthermore, the links in Type 3 e-mail are link to next registration step, link to privacy policy, link for inquiry about the email (i.e. the manufacturer’s web site). In Type 2 email, there was another link to cancel registration or delete user profile. Hence, this additional link to stop registration could also explain lower step conversion rate in Type 2.

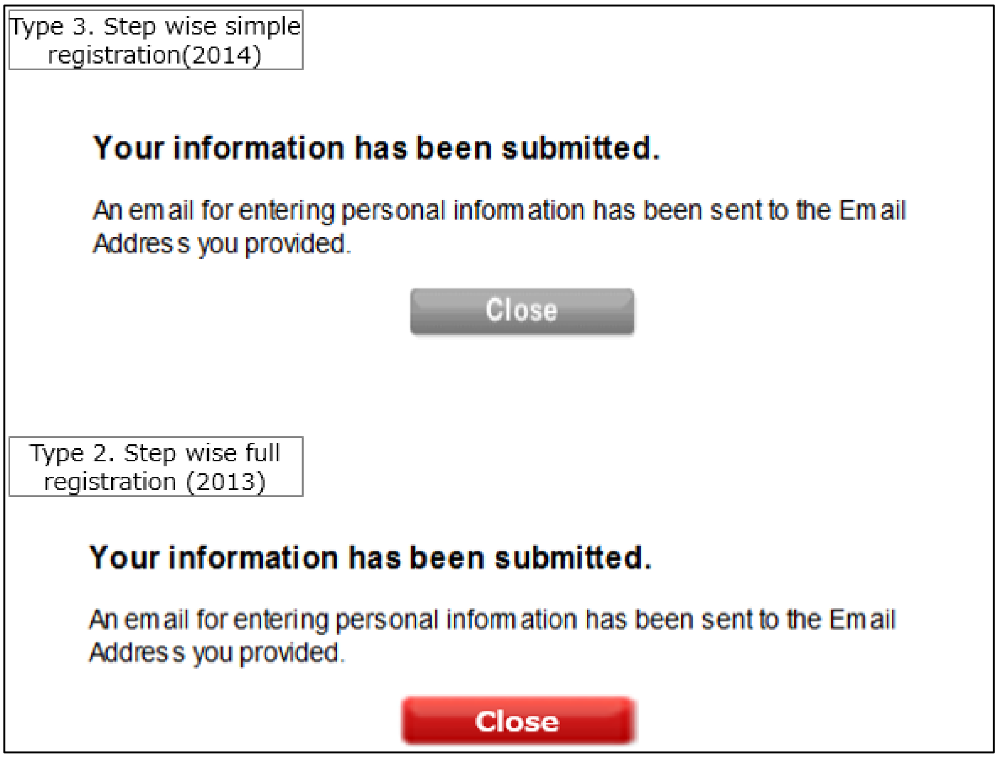


Figure 51. Temporary Completion Step

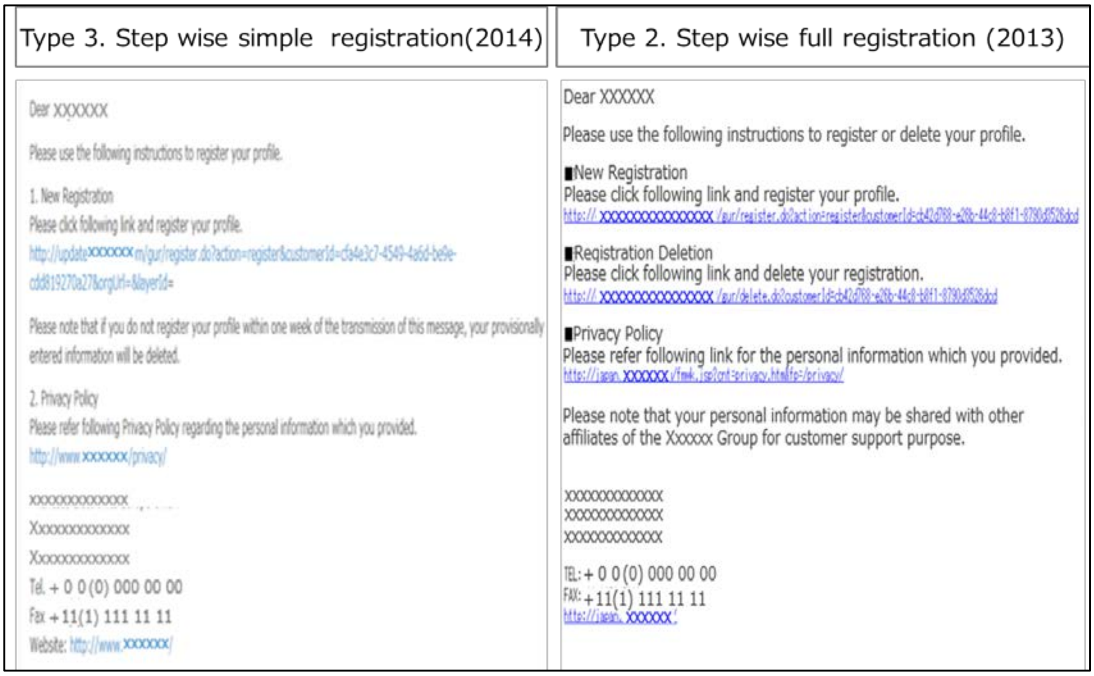


Figure 52. Temporary Completion Step

Lastly, I identify a step conversion rate gap in the last couple of steps in table 18. Type 3 registration process has 94.8% step conversion rate from 1,755 service registration page visitors and 1,664 completion page visitors. On the other hand, benchmarking Type 2 has 1,509 visitors and 987 visitors that give 65.4% respectively. One possible causation for the higher step conversion rate of Type 3 process is that it has less input fields. In fact, Type 2 has six input fields, none of which is required. Type 3 has two input fields, all of which are required fields. Nonetheless, I believe that having less input fields does not concretely explain higher conversion rate for Type 3 because visitors are required to select at least couple of services in the Type 3 step. When an input field is optional on registration form, then visitors are able to proceed even if they forget to select or enter one. However, when it is a required field, if visitors forget to select or enter a field, then they see error. In such a circumstance, not all visitors are taking time to fix error but rather exit. In short, having additional required fields on registration form could bring conversion rate down. Aside from the number of input and required field, we argue that the higher step conversion rate is resulting from clarity and usability of the registration form.

In Figure 53, I illustrate service preference registration form at the fifth steps. Type 3 form asks visitors two kinds of questions. One is about product selection for which visitors would like to receive communication. Visitors see general product categories such as “Micro-Processing Unit (MPU)” and “Software and Tools” with expandable nodes. Once a node is clicked, the node expands selected product category and shows manufacturer’s specific product categories in order to narrow down product selection. The other question is about application for which visitors are interested in. Visitors are to choose type of usage from checkboxes. At the bottom of the page, it has two buttons. One is to undo selection. The other is to proceed to next step highlighted in green. On the other hand, Type 2 form has a single question with sentences of instruction. It asks visitors to register for preferred services.

There is a structured pull-down set of fields at the top. These fields are labelled with mixture of general and manufacturer’s specific product categorization. At the middle of the page, there is a table to store selected product categories with a link to reset product selection. Furthermore, Type 2 form has an area for selecting application and customer support services including newsletter below the table. At the bottom of the page, it ends with three buttons. One is to cancel registration. Another is to go back to previous step. The other is to proceed to next step. These buttons are all coloured in red.

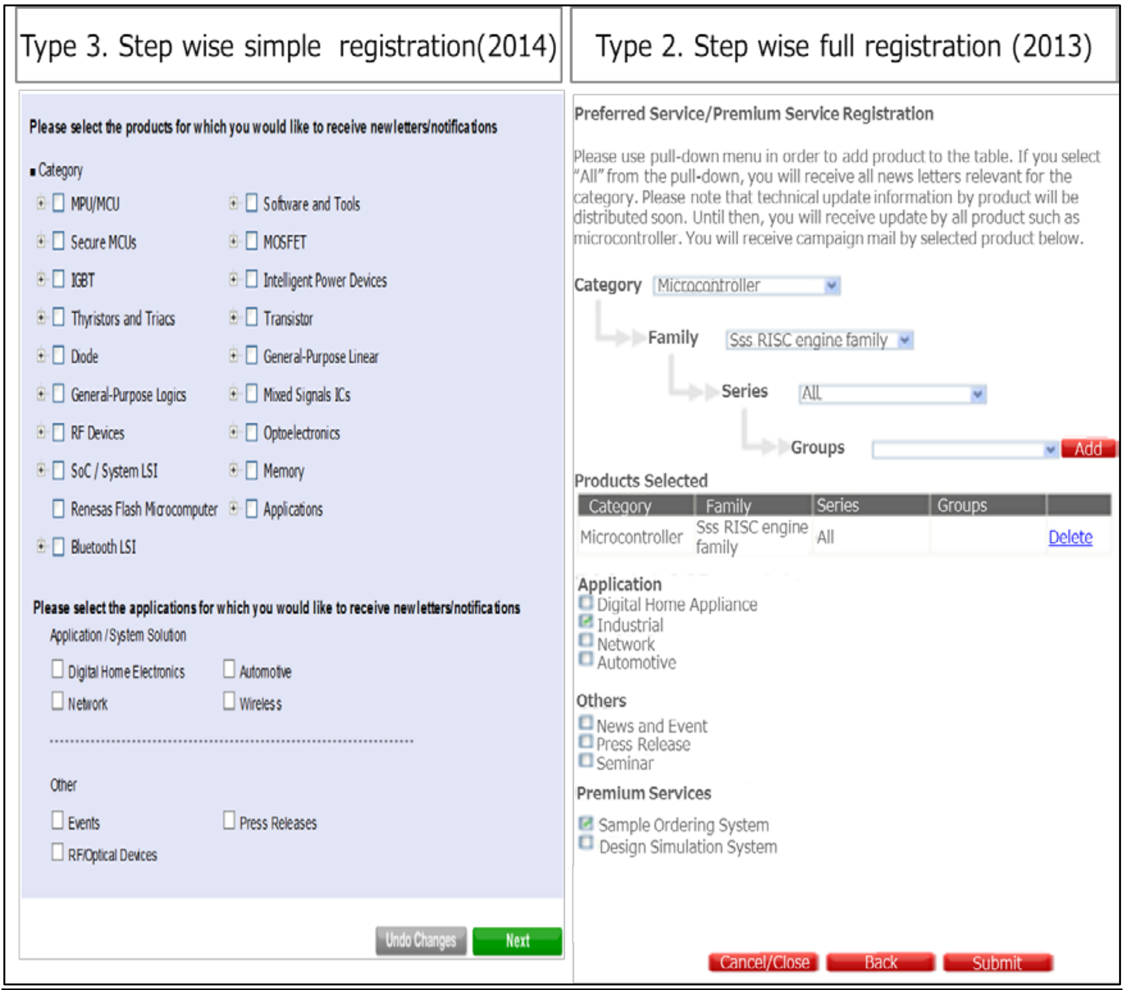


Figure 53. Service Information Registration Step

Given the above user interface and orientation of registration forms, I believe that Type 2 form was relatively more complex and confusing than Type 3 form such that Type 3 has higher conversion rate. For instance, the Type 2 page asks visitors to select product from the pull-down fields and to store selected product in the table even for those visitors who are unfamiliar with the manufacturer's product offerings. In addition, an interaction of pull-down fields and the table repository may not be obvious for first time visitor without reading through the instruction.

In addition, the manufacturer's product terminologies applied to pull-down fields' name makes production selection difficult for unfamiliar visitors. Moreover, the three buttons located at the bottom of the form are not differentiated because they are coloured same. Therefore, I supposes usability of Type 2 form was a causation for lower step conversion rate. Additionally, those buttons even offer cancelation of registration as well as revert to previous page that contextually bring step conversion down. I believe that website design norm “If you confuse them, you lose them” is true. This saying highlights an important website or service design perspective. In other words, designer has to pay special attention to customer’s usability by understanding customer’s language as opposed to that of business when they design website or service (Price, 2008).

In table 20, I have conducted follow-up research and analyzed different set of data for Type 3 form. It shows visitors’ registration tendency by timeframe. There are about two thirds of visitors who have registered to the manufacturer’s service on same day or less than one day of first visit. In addition, their conversion rates are approximately 67%.

Although, I have traced registration for another week and even for a month and more, conversion rates are greater than 67%. Possible reasoning behind this registration tendency is that visitors who have entered the registration process are eager to finish registration process. In other words, visitors are urged to use the manufacturer’s online services such as technical document download.

Table 20. Visitor Conversions by Timeframe

Registration Timeframe	Visit	Register	Conversion Rate
Day of Visit	861	582	67.60%
Less than 1 day	624	418	66.99%
Less than 7 days	311	212	68.17%
Less than 30 days	230	157	68.26%
More than 30 days	256	174	67.97%
Total	2,282	1,543	67.62%

5.4. Chapter Summary

As we have seen above, on-line user registration form is a critical marketing entry point for B to B manufacturer because it allows not only to filter registered website visitors from non-registered but also to communicate to them.

In this study, I have pointed a case from manufacturer and investigated initial situation where the firm had non-negligible exit rate due to the demanding on-line user registration form. I have historically tracked the manufacturer's on-line registration forms and their resulting figures such as number of visitors and relevant conversion rates. Then, I have analyzed the context and content of the manufacturer's web registration forms using those web registration form metrics as key. From the context perspectives, I demonstrated that number of registration steps, number of input fields and number of required fields, could be a factor of the conversion differences.

Furthermore, we found type of information being asked, embedded external links and registration form usability are critical factors from content viewpoint. Henceforth, given this result of registration form conversion study, I intend to look into other web conversion factors including document downloads, seminar registration, and sales inquiries and so on. In addition, I tend to study for relationship between registration timeframe and customer business momentum. For instance, if customers are urged to use manufacturer’s web service, then the customers are at later stage of their project than other customers are. Then, I aim for studying and publicly communicating those practical B to B marketing topics.

6. Conclusion

I have tried to clarify methodology on web analytics for B to B web site. I have two following premises for values of web analytics for B to B manufacturer companies. (1) Improve and optimize the site in user behavior and (2) Use in marketing activities like as knowing user requirements.

Visitors to B to B web sites have a variety of goals and web site requirement has different characteristics from B to C like more over-session accesses.

Firstly, I developed web analytic framework including path analysis, participation to conversion, user registration analysis for carrying out site optimization for usability and making use of data for marketing. I confirmed that especially user registration is important.

Next, I tried to use page dwell time as additional KPI metric as well as typical KPI metrics. Also confirmed page dwell time is effective to measure user stickiness to web sites. In particular, page dwell time is much related to various types of conversion in a B-to-B site. In addition, when we think about website structure improvement, looking at page dwell time can be one good metric. We can test usability or expected page flow with the results of dwell time as well as page views.

In addition, I developed analytic segmentation model and examined web access effectiveness using some segments like information, user environment, user behavior, and business.

One of the most important segmentations is registered users versus unregistered users. User behaviour is very different with each use case. Bounce rate, referrer (how they reach the site), and exit page analysis especially are beneficial and we can see that registered customers' stickiness to the site/company is much stronger than that of unregistered users. This can be measured by some metrics by segment, like duration of visit.

I surveyed correlation of access by user environment. There are correlations between time of day or correlation between connection types such as connecting through a provider or through a company network. I used some key web metrics such as visits and page dwell time for our correlation survey. I noticed user environment segments with a correlation approach can be used for web analytics for user navigation studies or even marketing use.

Finally, I have pointed a case from manufacturer and investigated initial situation where the firm had non-negligible exit rate due to the demanding on-line user registration form, which is important user behaviors for manufacturer site. I have tracked the manufacturer's on-line registration forms and their resulting figures such as number of visitors and relevant conversion rates. Then, I have analyzed the context and content of the manufacturer's web registration forms using those web registration form metrics as key. From the context perspectives, I demonstrated that number of registration steps, number of input fields and number of required fields, could be a factor of the conversion differences. Furthermore, I found type of information being asked, embedded external links and registration form usability are critical factors from content viewpoint. Since there was little study for B to B web analytic and basic methodology for it is. Methodology is provided with actual data in this study.

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Related Achievement List

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