Aalto University
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Using web analytics to measure, value and improve the performance of a business-to-business website

Master's Thesis
Espoo, May 20, 2013

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ABSTRACT OF
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Companies are struggling with decisions about web sites. Web analytics is a study about visitor online behavior and one of its key benefits is that decisions can be based on facts instead of opinions. This thesis was done for Company that was interested in facilitating web analytics to better guide decision-making.

The thesis can be divided into three parts: the first is about measuring web site usage, the second is about estimating the monetary value of web site usage and the third is about improving the business performance of the web site. We used A/B testing methodology to improve the web site performance.

A web site valuation framework was developed for this thesis. The framework contains two subcategories: revenue generating usage of the web site and cost saving usage of the web site. The framework is based on measuring the amount of important actions that visitors complete on the web site and on estimating the monetary value of those actions. A product purchase or a brochure download are examples of important actions. The framework provides multiple formulas to estimate the monetary value of those actions.

We found out that web analytics is a useful and powerful tool for web sites and basic web analytics is relatively easy to implement. However, to fully leverage the potential of web analytics site-specific customizations and manual labor from analyst is needed. We also found out that business-to-business web sites can benefit from A/B testing. We were able to improve the effectiveness of the "request a quote" form. One of the findings was that it is possible to estimate the monetary value of business-to-business web site even though the web site does not have e-commerce capabilities. Traffic observations also revealed some interesting insights: visitor behavior is improved when they are browsing the web site in their local language, visitor behavior is improved when the web site is fast and providing responsive design to mobile visitors is important as the usage of mobile devices to browse the web is increasing rapidly.

Keywords:	web analytics, web metrics, web site valuation, experimentation, experimental design, A/B testing
Language:	English

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Yritykset kamppailevat päätösten kanssa, jotka koskevat verkkosivuja. Web-analytiikka on oppi vierailijoiden online-käyttäytymisestä ja yksi sen tärkeimmistä hyödyistä on se, että päätökset voi perustaa faktoihin mielipiteiden sijaan. Tämä diplomityö on tehty Yritykselle, joka on kiinnostunut hyödyntämään web-analytiikkaa päätöksenteossa.

Työ voidaan jakaa kolmeen osaan: ensimmäinen osa kertoo Yrityksen verkkosivuston käytön mittaamisesta, toinen osa arvioi verkkosivun käytön rahallista arvoa ja kolmas osa kertoo web-analytiikan käytöstä verkkosivuston liiketoiminnan parantamiseen. Tässä työssä käytettiin A/B-testausmetodologiaa verkkosivuston parantamiseen.

Verkkosivuston arviointimalli kehitettiin tätä työtä varten. Malli koostuu kahdesta osasta: liikevaihtoa kasvattava osa verkkosivuston käytöstä ja kuluja säästävä osa verkkosivuston käytöstä. Malli perustuu siihen, että mitataaan, kuinka paljon vierailijat tekevät tärkeitä toimintoja verkkosivuilla ja siihen, että arvioidaan näiden toimintojen rahallista arvoa. Tuotteen ostaminen tai esitteen lataaminen ovat esimerkkejä tärkeistä toiminnoista.

Työn aikana selvisi, että web-analytiikka on hyödyllinen ja tehokas työkalu verkkosivuille ja web-analytiikan käyttöönotto on suhteellisen helppoa. Web-analytiikan täysi hyödyntäminen vaatii kuitenkin sivukohtaisia kustomointeja ja manuaalista työtä analyytikolta. Tulokset paljastavat, että A/B-testaus on hyvä tapa suorittaa kokeita verkkosivustoilla ja yritykseltä-yritykselle -verkkosivustot voivat hyötyä siitä. Löysimme myös, että on mahdollista mitata yritykseltä-yritykselle -verkkosivuston rahallista arvoa, vaikka verkkosivustolla ei olisi verkkokauppaa. Liikennetarkkailun tulokset paljastivat muutamia mielenkiintoisia näkemyksiä: vierailijat käyttäytyvät enemmän toivotulla tavalla, kun he selailevat verkkosivustoa paikallisella kielellä tai silloin, kun verkkosivusto on nopea ja mobiililaitteille optimoidun käyttökokemuksen tarjoaminen on tärkeää, koska mobiililaitteiden käyttö verkon selailuun kasvaa räjähdysmäisesti.

Asiasanat: web-analytiikka, web-mittarit, verkkosivuston arvon arviointi, kokeellinen suunnittelu, A/B-testaus

Kieli: Englanti

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I have enjoyed writing the thesis. The journey to the world of web analytics has been interesting, and especially the results from A/B tests have been surprising. As a student of technology it has been nice change to study the human behavior instead of machine behavior.

I want to thank my employer HiQ Finland Oy for giving me the chance to step aside from day-to-day work and to concentrate on my thesis. I want to thank Jan-Erik Lindfors, Olli Laine and Nira Biaudet for making this possible.

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Espoo, May 20, 2013

Panu Vuorinen

Abbreviations and Acronyms

B2B	Business-to-Business
BR	Bounce Rate
CDN	Content Delivery Network
CPU	Central Processing Unit
CR	Conversion Rate
CRM	Customer Relationship Management
CSS	Cascading Style Sheets
DOM	Document Object Model
FF	Firefox
GA	Google Analytics
HTML	HyperText Markup Language
HTTP	HyperText Transport Protocol
IE	Internet Explorer
KPI	Key Performance Indicator
OKR	Objective and Key Results
PII	Personally Identifiable Information
SAAS	Software as a Service
URL	Universal Resource Locator

Contents

Chapter 1

Introduction

The internet and World Wide Web have become important global communication channels. Nowadays they are used by both businesses and individuals making the internet an important place for business. Most businesses have a web presence and business goals for it. In the past companies had only a web site, but nowadays web presence contains also visibility on search engines and visibility on social media as both are popular and therefore important traffic sources for web sites. In the past, corporate investment in web sites was just seen as something you had to do, whereas now, instead of blindly investing, businesses want to measure, value and optimize their web presence.

1.1 Web analytics

The internet makes it possible to know every interaction the site visitors have with the site. Marketers have not had such an information-rich channel to analyze the visitor behavior before. For traditional media, like newspapers, radio and TV it is difficult to evaluate success. With web analytics on the internet, this becomes relatively easy: practically everything can be measured [11]. It is to be noted, however, that the increased amount of data does not necessarily lead to better insights or better decisions. The amount of data can also be overwhelming and interpreting data requires expertise.

Web analytics is a study of online visitor behavior. It consist of collecting anonymously web site usage, aggregating and reporting it, and finally analysing results [5]. With web analytics it is possible to gain data that cannot be obtained elsewhere. Web analytics is a relatively new field and it has been under rapid development. It is a very commercial field and driven by technological advancements and commercial interest, not by academic interest.

1.2 Motivation

Companies, especially companies whose core competence is not in technology or in the internet, are struggling with decisions about different aspects of web sites [29]. Web analytics collects visitor usage behavior and therefore enables the decisions to be based on actual data, instead of opinions. According to leading practitioners in web analytics, experts are not very good at predicting user behavior, and the core benefit of using web analytics is to base decisions on real usage data [11, 29].

This thesis is done for a global Finnish manufacturing Company. The Company is public and it is listed to Helsinki Stock Exchange. Company executives are interest in the benefits of web analytics and the Company has already facilitated simple web analytics. However, they want to know if the benefits of web analytics can be better realized with further work. The purpose of this thesis is to apply customized web analytics to the Company website. The focus on research is on the business benefits of website. The Company web site is researched as a case study.

1.3 Problem statement

The focus of this study is to use web analytics to support the business of the website. We have defined three research questions:

1. How to study web site behavior using web analytics?
2. How to improve web site performance using web analytics?
3. Can web analytics be used to measure B2B web site's commercial value?

For this study we have taken three approaches, based on research questions. The first approach is about studying the usage of the web site and trying to find insights – focusing on the past. The second approach is to use web analytics to improve the performance of the website. That is, the second approach focuses on the future. The third approach, valuing the web site usage, focuses on the past and on the future. The ambitious objective is to value the web site usage using monetary value. With that information it is possible to calculate return on investment for previous investments and also to evaluate future investments and development ideas.

1.4 Structure of the Thesis

Chapter 2 provides background information about web analytics, both from an academic and a practical point of view. Chapter 3 introduces the research methods used in this thesis: web site valuation, exploratory behavior analysis, traffic source analysis and A/B testing. Chapter 3 also introduces statistical significance. The next chapter, Chapter 4, presents the environment for the thesis: Company, web site, metrics, goals and valuations and web usage data. The next chapter, Chapter 5 presents the results acquired by web analytics measurements. This chapter introduces and explains measurements in exploratory behavior analysis, in traffic sources and in A/B tests. Chapter 6, analysis, provides analysis that analyzes the measurements in Chapter 5, combines results together from different measurements and reflects results in context of information from background chapter. The discussion chapter, Chapter 7, ties the work combining data from all chapters. It answers research quoestions, presents the generalizable results from Chapter 5, evaluates used methods and literature, assesses the contributions of the thesis and also predicts the future of web analytics. Chapter 8 wraps up the thesis and draws conclusions.

Chapter 2

Web analytics background

This chapter provides the reader with background information about web analytics. It is required reading in order to understand the thesis. The first section places web analytics in a data mining context to provide an academic context for the thesis. The second section tells about the history of web analytics, and then the chapter describes the technical background of web analytics, introduces different usage tracking methodologies and discusses related data accuracy issues. Then it tells about the history of web analytics, lists benefits and use cases, introduces standard web metrics and discusses good metrics, and finally introduces the goals of web analytics, key performance indicators. After that the chapter presents the current state of the industry, ponders about privacy issues in web analytics and introduces controlled experiments.

2.1 Web analytics in Data Mining context

As a broad definition, data mining in general refers to extracting or "mining" knowledge from large amounts of data. The general goal of data mining is to get meaningful information from data sets. [20] Web data mining means extracting knowledge from internet sources. Web data mining can be divided into three sub-areas: web structure mining, web usage mining and web content mining. Web content mining analyzes hypertext and text documents, web structure mining analyzes link structure and web usage mining analyzes interactivity. Web usage mining in academia has the same meaning as the term web analytics in commercial world. Figure 2.1 sets web analytics in a data mining context. The figure was first introduced in Laura Kainulainen's master's thesis [25]. [34]

Web analytics as a field is currently under rapid development driven by strong commercial interests. Scientific literature and academic journals tend to be at least partly outdated. Especially the web analytics tools that vendors offer are constantly being updated. Also the trends in web analytics and related fields come and go quickly. Up-to-date information can be found from online, mainly from professional and vendor blogs.

Web analytics is about measuring and collecting clickstream data, reporting and analysing it for the purposes of understanding and optimizing web usage. Kaushik [29] introduces his term "Web analytics 2.0" and argues that web analytics are developing to a direction where web analytics not only include clickstream data but also competitor information and social media monitoring. Another practitioner, Brian Clifton [11] mentions that web analytics is futile if not used to support business decisions emphasizing the commercial nature of the field.

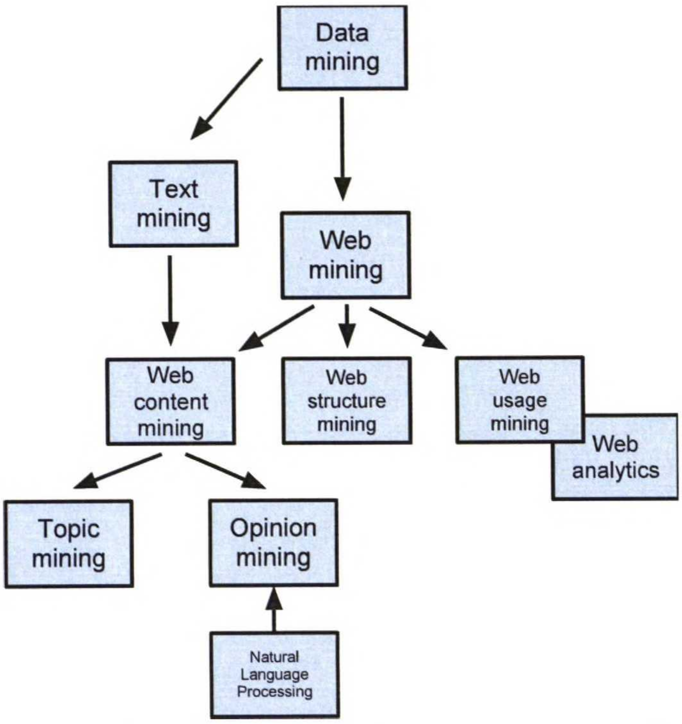

Figure 2.1: Web analytics in data mining context. [25]

2.2 History

Many of the studies about web analytics made before the year 2008 focus on issues related to web analytics and discuss reasons why web usage data is underutilized even though it has clearly identified benefits. Articles "Current trends in web analytics" [56] and "Web usage statistics: measurement and analytical techniques issues" [8] argue that the incompleteness of data in weblogs-based mechanisms, like unavailability of cached page requests and overavailability of bot page requests, separating referrals and large data size lead to underutilization of clickstream data. Norguet et al. argues that data based on page-based audience metrics suffer from page synonymy, page polysemy, page temporality and page volatility leading the web analytics reports to be too detailed to be exploited by managers [43]. A study by Weischedel et al. revealed a number of serious limitations to the collection and usage of web log data [61]. They also found out that managers highly regard the use of web analytics and are eager to find out how to utilize it more. Welling et al. (2006) researched a broad spectrum of company types and sizes and found out that web site performance measurement is largely underdeveloped and/or completely ignored [62].

Since 2008 the tools and methodologies have improved. The page tagging-based data collection has replaced weblogs-based data collection as the de facto standard to address weblogs methodology's problems (see table 2.1). The shift from web logs analysis to page tagging-based data collection did not happen overnight, but the clear trend can be seen. The release of Google Analytics in the end of 2005 and its popularity have contributed the page-tagging's dominance [19].

Kaushik's view on history of web analytics is based on technological advancements: initially analytics focused on individual HTTP requests, hits. Nowadays one page load can trigger dozens of HTTP requests, but back then web pages consisted of only 1 HTML page. However, that vastly exaggerated the amount of visitors. The next phase was to concentrate on page views. That was also inaccurate, because refreshing page would increase the page view count. Later phases concentrated on actual visits and on actual visitors. The recognition of the difference between visits and visitors made usage tracking analysis more accurate. The latest trend is to focus on outcomes instead of the amount of visitors. [29]

2.3 Technical Background

This section describes web usage tracking methodologies, discusses their advantages and disadvantages and then helps the reader to understand the accuracy issues within web usage tracking.

2.3.1 Usage tracking methodologies

Web page usage data can be grouped into three different methodologies: page tags (sometimes called web beacons), logfiles and packet sniffing. Easy availability of web server logs and availability of freeware log analyzer made logfile analysis the most popular among methodologies in the past. Such freeware log analyzers are, for example Webalizer, AWStats and Analog. In recent years, the page tagging methodology has become increasingly popular and nowadays page tags are the de facto standard for collecting visitor data. Packet sniffing was never very popular, but it has its strengths and it is still used. [11, 16, 29, 60]

Page tags collect data using the visitor's web browser. Page tag collects information about visitor using web browser and sends the information to remote data-collection servers. The remote server collects data and analyzes it. Data analysis can be real-time at best, but usually analysis is calculated in batch jobs a couple of times a day, making it appear to the web analytics end user that it takes hours to analyze. The delay is not processing delay, instead the batch jobs that analyze data are run on certain intervals. The analytics user can then view reports from remote servers. Usually page tagging information is captured with JavaScript and sent using Ajax to a remote server. A web site owner has to include page tagging script to all pages of a web site. Page tag solutions also typically use cookies to identify visits from the same visitor. Some vendors also offer the possibility to customize the collected data with custom tags. A page tags solution is usually bought as an external, software-as-a-service (SAAS) solution. Figure 2.2 is a visualization of the page tagging methodology in action.

Logfiles contain data collected by a web server. Logfile data is independent from the visitor's browser. This methodology collects data from the server-side, so it captures all requests to web server, including pages, PDF files, images and erroneous requests. Logs also contain information on bandwidth usage. Logfile analyzer software is needed to analyze collected data, to compile it to reports and to show it to the analytics user.

Packet-sniffing-based solutions collect raw packet data between the web server and the web site visitor. This is usually accomplished with a hardware-

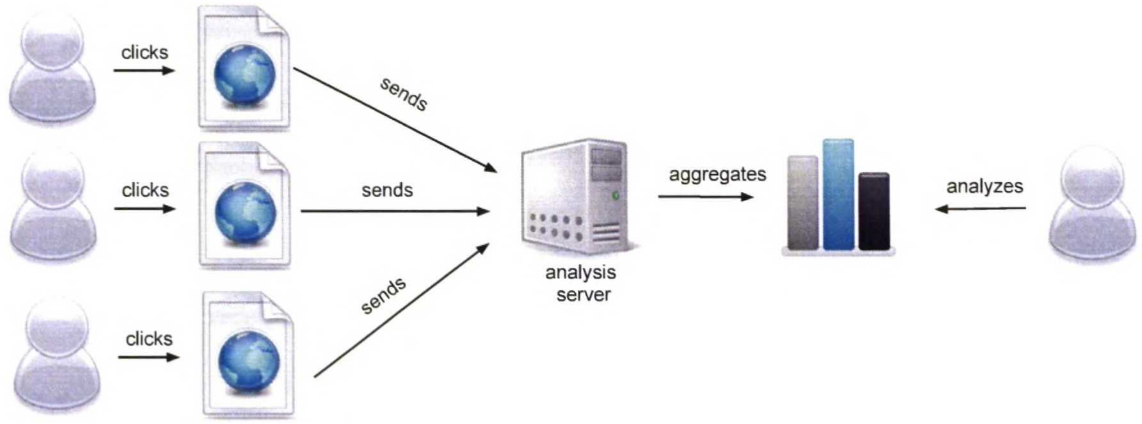

Figure 2.2: Page tagging data collection visualization.

based solution: a platform is placed between the web server and the internet. Also software-based solutions, that add another software layer, are available. Packet-sniffing-based-solutions do not necessarily require web site owners to modify the web site at all and reports are usually available right away. The data is collected, analyzed and viewed on-site. This solution is nowadays so rare, that only a few web analytics books even list this as a possible web page usage tracking methodology.

Even though page tagging is by far the most widely adopted methodology nowadays, each methodology has its own strengths and weaknesses. Some vendors offer multiple methodologies to track visitor's behavior more comprehensively. The tables 2.1 and 2.2 summarize the advantages and disadvantages of each methodology. Table 2.1 has been adapted from Clifton's book Advanced Web Metrics with Google Analytics [11] and table 2.2 was adapted from Shilpi Ganguly's article "Collecting Data Using Packet Sniffing" [16].

2.3.2 Data tracking accuracy

This section discusses issues in data tracking accuracy in web analytics. The emphasis is on data tracking accuracy issues in page tagging methodology, because that is both the de-facto standard nowadays and the selected tracking methodology for this thesis.

Page-tagging specific issues include issues with JavaScript, firewalls and cookies. A single JavaScript error on a page renders page-tagging methodology unusable on the current page. During a visit losing a single page can make a visitor's single visit to appear twice in analytics reports. Private or corporate firewalls can block the calls to web usage tracking service preventing the page tags from functioning at all. The web usage of visitors with very restrictive firewalls cannot be tracked with page tagging mechanism. Cookies are a widely accepted method to recognize visitors. However, users can reject or delete cookies making unique visitor tracking unreliable. [11]

Methodology	Advantages	Disadvantages
Page tags	• Breaks through proxy and caching servers - provides more accurate session tracking. • Tracks client-side events - like JavaScript, Flash, AJAX. • Allows the vendor to program updates against you. • Allows the vendor to perform data storage and archiving for you. • Collects and processes visitor data in nearly real time.	• Web pages require modification. You have to make changes to your web site pages (add tags) in order to collect data. • Setup errors lead to data loss. If you make a mistake with your tags, data is lost and you cannot go back and reanalyze. • Cannot track bandwidth usage or completed downloads. Tags are set when the page or file is requested, not when the download is complete. • Cannot track search engine spiders. Robots ignore page tags. • Firewalls can mangle or restrict tags.
Logfile analysis software	• Automatic data collection. Does not require any changes to your web pages. • Historical data can be reprocessed easily. • No firewall issues to worry about. • Can track bandwidth and completed downloads, and can differentiate between completed and partial downloads. • Tracks search engine spiders and robots by default. • Tracks legacy mobile visitors by default.	• Proxy and caching inaccuracies. If a page is cached, no record is logged on your web server. • No event tracking - for example, no JavaScript, Flash or AJAX tracking. • Requires your own team to perform program updates. • Requires your own team to perform data storage and archiving • Robots inflate visit counts and this can be significant.

Table 2.1: Advantages and disadvantages of page tags and logfile analysis software methodologies.

Methodology	Advantages	Disadvantages
Packet-sniffing-based solution	• Since all data passes through the packet sniffer, it eliminates the need to use JavaScript tags for your web site. Does not require any changes to your web pages. • A huge amount of data can be collected instantly, more than with JavaScript tagging. For example, server errors and bandwidth usage data. • You will always have the ability to use first-party cookies. • No data loss due to erronous page tagging. • Historical data can be reprocessed easily.	• It requires additional layer of software or physical hardware between web server and the web. • As packet sniffer collects raw IP packets, the amount of data is huge. It requires potentially complex site-specific configuration work to filter unnecessary packets. • Raw data captures all data, also Personally Identifiable Information like names, passwords and addresses. Privacy requires stress testing and legal review. • With multiple web servers or multiple web server locations the installation cost rises because packet sniffer has to be installed on all of the networks. • Requires page tags to collect data about cached pages.

Table 2.2: Advantages and disadvantages of packet sniffer methodology.

In general, web analytics' accuracy suffers from users with multiple devices, different users using same device or same user using multiple browsers. The rise of mobile devices increases the amount of devices the same user uses. These issues cannot be tackled with anonymous web usage tracking. They can be tackled by requiring visitors to register, but that is not a practical solution for many web sites. [11]

Because of these accuracy issues, current tools tend to significantly overestimate the amount of unique visitors [11] [15]. It is also known that absolute values for different web metrics vary between different vendors. Trends over time, however, tend to be more alike and comparable between different tools and even between different methodologies.

Usually it is only of interest to track the usage of anonymous visitors, not visits from administrators, content editors or company employees. These non-desired users can be filtered out by setting up IP based filter lists, filtering out certain referrals, disabling the page tags for logged in visits or implementing a custom browser header. None of these methods is 100% accurate, but they can be used to filter out most of non-desired visitors.

2.4 Practical approach

This section describes web analytics in practice. First it provides general information about business usage of web analytics and then it leads the reader through standard web metrics. Following this general information is a discussion about the quality of different metrics and finally the section describes the goals of web analytics, key performance indicators.

Typically web sites serve multiple user groups and multiple desired behaviors, goals. Big, commercial web sites tend to have a huge number of visitors and the amount of data can be overwhelming. The key to analyzing big data is segmentation. Segmentation can be classified to three segmentation strategies: segmentation by source, segmentation by behavior and segmentation by outcome. For example segmentation by outcome can be used to find out what converted visitors [1] have in common. [27]

2.4.1 Benefits and use cases

With web analytics it is possible to measure all kinds of usage on a web site. Practitioners argue that the main benefit of web analytics is the ability

[1] Converted visitors means the group of visitors that have completed a wanted behavior, a goal, e.g. bought a product from e-commerce site.

to base decisions on actual data instead of expert opinions [2]. Clifton even argues that web analytics is futile if it is not used to support business decisions. Kaushik recommends that one should focus on and measure outcomes, because measuring outcomes connects customer behavior to the bottom line of the company. Basically, every commercial web site attempts to deliver three types of outcomes: 1) increase revenue, 2) reduce cost and 3) improve customer satisfaction or loyalty. [11, 29]

While many studies recommend the use of web analytics to evaluate and measure web site performance, few studies have focused on outcomes or on supporting decision-making, as recommended by experts [29] [11]. A large number of studies show the benefits of web analytics: web analytics can, and should, be used to improve web site usability [14, 21, 23, 44, 53], to increase web site conversion rates [17, 21, 64], to measure web site value [62, 64], to improve strategic communication and public relations [31], to measure the effectiveness of traffic sources [47] and to evaluate web site performance [23, 35, 44, 46, 48, 64, 66].

For example, Wilson was studying an airline company web site as a case study in his article "Using clickstream data to enhance business-to-business web site performance". He ran three tests with control groups and found out that conversion rates can be influenced by both web site design and by specific market tactics designed to make the online shopping experience more appealing. In the case study the web site design improvements raised conversion rate by 40% whereas free delivery campaign raised conversion rate by over 50%, and, more importantly, it raised the average order value and average order quantity of items. Wilson concludes that clickstream data can not only be used to assist with web site design and evaluation; it can be used to guide the development of an entire internet marketing strategy. As one can track almost everything with web analytics, he raises the issues of privacy and ethics in analytics that violate Personally Identifiable Information (PII). [64]

Usability labs are traditional method to assess the usability. Gofman et al. argue that using experimental design for web site optimization is a better approach than usability labs. According to their article, using usability labs rarely results in disastrous design, but it also rarely results in exceptionally good design. Using experimental design and measuring it with web analytics is the recommended method to drive desired behavior on web sites. [17]

[2] Kaushik [29] notes that decisions based on usage data tend to be better than decisions based on HiPPOs (Highest Paying Person's Opinion).

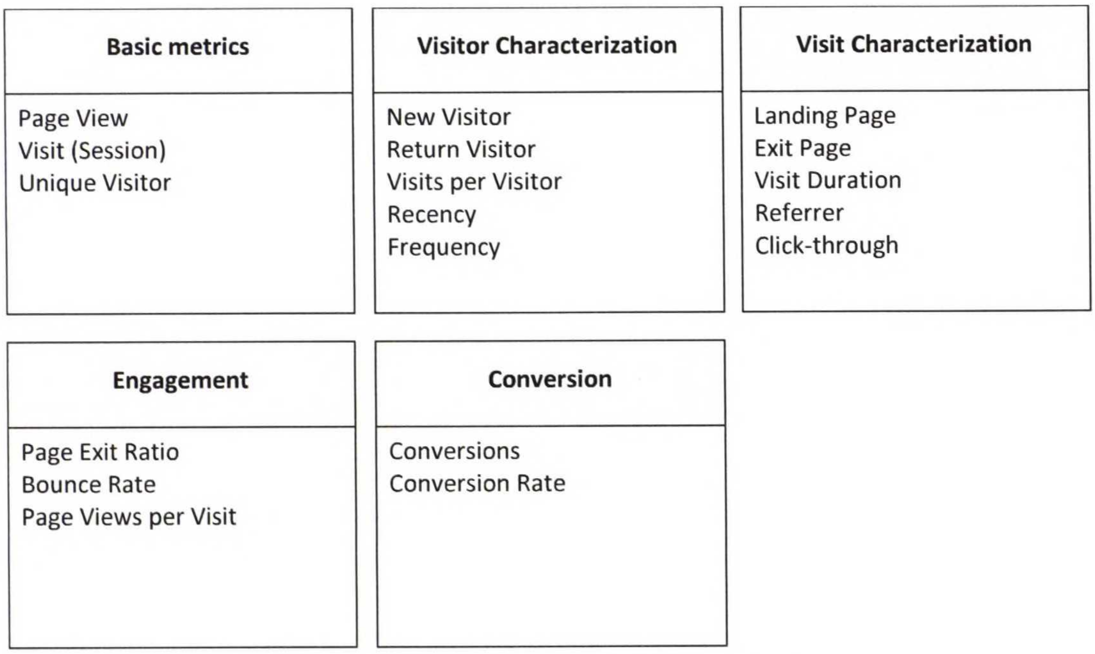

Figure 2.3: Standard web metrics as defined by Web Analytics Association.

2.4.2 Metrics

The Web Analytics Association has defined standards for web analytics. [5] The organization takes pride in enabling common ways of looking at data measurement and methodologies. Thus they enable compatibility of results among different tools, more meaningful industry benchmarking and better understanding of the metrics terms we all use. In practice the different metrics between different vendors are not comparable [29].

Most vendors offer standard metrics. However, commercial vendors want to differentiate themselves by providing something on top of these standard metrics. These custom solutions make the comparisons more difficult between different tools.

2.4.2.1 Standard web metrics

Web metrics are based on three standard metrics: *page views*, *visits* and *unique visitors*. Page views tell the number of times visitors have viewed web pages, visits tell the number of sessions and unique visitors tell the absolute number of unique users.

The Web Analytics Association divides other standard metrics to four dimensions: visit characteristics, visitor characteristics, engagement and conversion. Visit characteristics contain *landing page*, the page where visitor started the session; *exit page*, the page where visitor quit the session; *visit duration*; *referrer*, the web page where user entered the web site, if any; and *click-through*, the amount of clicks divided by the amount of views. It is to be noted that exits can be either good or bad exits: a good exit would be an exit on a thank you form after submitting a contact request, and a bad exit would be an exit on a front page.

Visitor characteristics contain five metrics: *new visitor*, a visitor that has not visited the web site before; *return visitor*, a visitor that has visited the web site before; *visits per visitor*, the number of times the visitor has visited the web site; *recency*, the amount of time since the last visit of a visitor; and *frequency*, the amount of actions per visitor. Visitor characteristics metrics are good for segmenting web usage.

The engagement dimension contains three metrics: *page exit ratio*, the amount of page exits divided by the amount of page visits without exits; *bounce rate*, the amount of visitors that left the site only viewing a single page; and *page views per visit*, the amount of web pages the visitor consumes on average. Bounce rate is one of the most important basic metrics: it tells instantly, which pages are not functioning to their full potential.

Conversion dimension contains two metrics: *conversions*, the absolute number of times that users have executed desired behavior (goal); and *conversion rate*, the ratio of visitors that execute desired behavior. Kaushik [29] introduces an important concept concerning conversions: micro and macro conversions. Macro conversions are the core targets of the web site, be it a subscription to feed, buying a product or leaving a contact request. Micro conversions are less important for business, but equally important to measure and they often lead the visitor to macro conversions. Examples of micro conversions are, for example, applying to a job, downloading a brochure and visiting feed subscription page. It is to be noted, however, that every web site has different goals and no must-have goals or definitive micro and macro categorization can be defined. The rationale behind micro conversions is that macro conversion rate is typically very low, 1%-5% of all visits - Kaushik recommends adding micro goals to track the rest of the traffic.

Most web metric values are not distributed according to normal distribution [3], but instead are more likely to be randomly distributed or long-tail distributed [11]. Therefore analyzing average values can be misleading. For example, average time on site can be low because of high bounce rate. But when segmenting bounced visitors away, the average time on site can rise considerably. [29]

[3] Also known as Gaussian distribution.

A survey of web site success metrics used by Internet-dependent organizations in Korea shows that businesses use mostly simple metrics. Out of 40 organizations they interviewed for results, 27 used visits metric, 24 page views, 5 used entry/exit IPs and only 4 used conversion rates - 10% of respondents. The study was from 2007 and use of advanced web analytics might have been improved afterwards. The study also notes that most of the businesses use web analytics merely for operational purposes, few use web analytics data for strategic purposes. [23]

2.4.2.2 Properties of good metrics

In this subsection we present multiple attributes to evaluate the usefulness and effectiveness of a metric. It is important to note that metric quality attributes presented in this subsection are not limited to, or even associated with, generic web metrics specified in the last subsection. These property attributes can be used to compare custom online metrics as well as offline metrics.

There are multiple definitions of good metrics and multiple guidelines on how to select good metrics. We will present here two different approaches: one from Eric Ries' book The Lean startup and one from Avinash Kaushik's book Web Analytics 2.0. Approaches are similar, but there are also some differences. Ries defines three attributes: *actionable*, *accessible* and *auditable*. Kaushik, on the other hand, defines four attributes: *uncomplex*, *relevant*, *timely* and *instantly useful*. [29] [51]

Both argue for the need of metrics to be as simple as possible, but not simpler. Kaushik calls this property "uncomplex" and Ries "accessible". Usually the decisions made in a corporate environment are not done by individuals alone; therefore, it is important that everyone understands the metrics that the decisions are based on. It is easy to make a report incomprehensible by using wrong kind of units.

Consider a web site that has 100 000 hits [4]. What does it mean? The number of hits is a bad metric. A better metric would be the number of visitors. A web site was visited by 5000 people. Now it is more understandable, but still it doesn't clearly tell us anything. An even better metric would be the trend of visits. Last month the web site was visited 5000 times, this month only 3500 times. Something is wrong, and this calls for action.

Another attribute that raised by both Ries and Kaushik is that a metric should be "actionable" (Ries), or "Instantly useful" (Kaushik). The metric should demonstrate clear cause and effect - otherwise is not actionable. If

[4] Hit is a single call to web server, for example a call to load image, JavaScript file or REST request. Contemporary web sites have typically dozens of hits per single page view.

the metric is instantly useful, it is easy to use and it drives action. It might take a lot of effort to mine the data and produce instantly useful metrics, but it is worth it. According to Kaushik, if the metric is not instantly useful, it will be instantly ignored instead.

Ries mentions third factor: metric should be "auditable". Analytics reports are usually tied to decision making. Therefore, the data that decisions are based on needs to be reliable. If people do not trust the data, then it cannot be used as a decision making factor and all work for that metric have been in vain. If the data is auditable, the data is more likely to be correct and people are more likely to trust it.

Metrics are different for each company, even in the same field. Kaushik introduces his third property, "relevant", and stresses its importance. It is important to use relevant metrics to your business. It sounds like it is self-evident, but it is not. It is easy to use the same, standard metrics for every business even though they might not be relevant or optimal.

Kaushik's fourth property is "timely". Nowadays businesses and customer demands move fast. It is important to have the reports in a timely fashion to make informed decisions. If the report based on metrics takes months to generate, the report is no longer useful when it is finished. Kaushik advices to sacrifice complexity and perfection for timeliness.

Typically raw counts are not good metrics. Raw counts tend to go up as web site's use base grows, and they need to be normalized to be effective and comparable. Ratios, percentages or averages per user are often more useful. [53]

2.4.3 Key Performance Indicators

The target of web analytics is key performance indicators, KPIs (sometimes called key success indicators, (KSI) or balanced score cards (BSC)). They enable integrating web metrics to the overall business objectives. Before selecting KPIs it is vital to define objectives and key results (OKRs). OKRs are the reasons that organization exists. For KPIs it is important to only consider OKRs that the web site can, or should, have effect on. For example, OKR can be "to sell more products", "to reduce the amount of support requests" or "to improve customer experience". Jackson [24] divides KPIs to visionary KPIs, which reflects company strategy and must be set by the company leaders, and tactical KPIs, that reflect goals and objectives. [11]

For a small organization a single dashboard containing five to ten KPIs is sufficient. Larger corporations tend to have many stakeholder groups with different needs. Stakeholder groups can be either inside the organization, like marketing or IT, or outside organization, like web design agency. Stakeholder groups will need their own dashboards. Dashboards should be hierarchical, so that senior executives are shown only a handful of key metrics whereas different stakeholder groups, like web site designers, are shown broader selection of metrics. [11]

Kaushik [29] provides a list of five, untraditional KPIs. First is task completion rate, the percentage of visitors to web site who rate if they were able to complete the primary purpose for their visit. It is not possible to accurately measure this KPI by clickstream data only; instead one should use a survey to find out the task success rate. Second is share of search: the percentage of traffic from search engines compared to key competitors' traffic. The point is to get comparable information. Third one is visitor loyalty and recency. Loyalty measures the distribution of the number of visits by each visitor and recency measure the gap between two visits of the same visitor. They help to measure the lifetime value of visitor. The number of RSS/Feed subscribers is the fourth KPI. This should be measured, because feed is usually out of range of analytics and feed subscribers indicate the most committed, valuable audience. Fifth KPI that Kaushik mentions is the percentage of valuable exits. It measures the percentage of visitors who leave the web site by clicking something of value to web site, like an advertisement.

2.5 Current state of the industry

Web analytics or analytics in general is a competitive environment. Today some vendors offer free and powerful web analytics tools, like Google Analytics [2]. Yahoo! provided similar free web analytics tool called Yahoo! Web Analytics, but they decided to discontinue it in June 2012 [59]. In addition to tools specializing in web analytics there exists powerful custom analytics tools like MixPanel [3] and BitDeli [1] - both are software-as-a-service offerings and chargeable services. The Finnish "Snoobi" [4] service is an example of a very specialized analytics service - it focuses only on generating sales leads from web site visits.

Search engines are strong traffic sources for most sites. Search keyword analysis is a critical part of Search Engine Optimization, the art of making web sites appear as high on search engine ranking as possible. At the end of 2011 Google decided to encrypt the search keywords from users that are signed in [26]. In practice the decision means that web usage tracking software cannot anymore track the search keywords from signed-in Google users. Nowadays a significant number of internet searchers are logged into Google. The numbers vary, but it's a significant part of internet users, somewhere between one third to half of internet users [55]. Google being the world's most popular search engine [41], this has clear implications to web analytics. The possibilities of keyword analysis are severely harmed, because one third or even more of the search keyword data is missing. [11]

The research survey of web analytics studies released after 2010 seems to indicate that currently the most used web analytics tool in studies is Google Analytics. Google Analytics is also the market leader in the private sector [7, 9, 38]. Google Analytics has been used in academia, for example, to measure tourism-related web site's usage [48], to compare publically funded food composition web sites [44], to analyze the usability of e-commerce sites [21] and to analyze user navigation paths [66].

2.6 Privacy considerations

There are two types of private information: personally identifiable information (PII) and non-personally identifiable information (non-PII). Both contain personal information and the former information can be used to identify a person, whereas latter cannot be used to identify a person. Non-PII information is general aggregate data collected from a group of people. For example, one could study the age, sex and color of clothing of voters and not violate the privacy. But when studying about the occupation, address or name of voters, the information turns to PII. [11]

Third-party tracking is tracking, where third party, like Google, tracks user behavior over multiple different site visits. Web analytics, as studied in this thesis, consists only of first-party tracking: that is, tracking only the visitors of one web site. Third-party tracking is criticized for compromising user's privacy and academically funded tools, like Sharemenot [54], have been developed to prevent third-party tracking.

Akkus et al. even went as far as introduced non-tracking web usage tracking methodology in their article "Non-tracking web analytics" [6]. Their approach gives users privacy guarantees, requires no new organizational players and is practical to deploy, but it has not gained widespread adoption since its publish in 2012.

Vendors have different approaches to PII. For example, Snoobi Analytics collects IP addresses, but only to recognize the company [4]. They claim that recognizing the company is not PII. However, European Union's group of data privacy regulators stated that IP addresses should be considered as personal data [49]. The debate is ongoing. Google Analytics takes a very strict line on collecting PII - it does not allow collecting PII even with explicit permission from site visitors [11]. If a site collects PII with user's explicit permission, it must be stored outside Google Analytics.

2.7 Controlled experiments

"One accurate measurement is worth more than a thousand expert opinions."
— Admiral Grace Hopper

Controlled experiments, also known as *experimental design* in marketing, *A/B testing* or sometimes *randomized experiments* are scientifically valid method to conduct experiments between variations to see whether there is a real difference between variations. [33]

Typically it is very hard to predict the user behavior. According to Kaushik, 4 times out of 5 the web site designer is wrong about what a customer wants [28]. Jim Manzi reports similar experiences: "Google ran approximately 12 000 randomized experiments in 2009, with about 10 percent of these leading to business changes" [39]. The same goes for Netflix, Mike Moran says that 90 percent of what they try is wrong [42]. It seems that designers are very bad at predicting user behavior and that speaks strongly on the need to rely on the results of controlled experiments instead of relying on expert opinions.

A/B testing, visualized in figure 2.4, is a testing methodology where different versions of testable subject are shown to randomly selected test groups. In its simplest case, there are two versions of the testable subject, say, a web page: A and B. The test group, web page visitors, is randomly divided to two groups: A and B, so that both groups contain 50% of the test group. The web page has to have a desired behavior, called a goal: for example, the test page can be a registration form and goal can be amount of registered users. Then the test is executed for long enough time to achieve statistical significance, as discussed in section 3.5. [5] The test result can be that either of A or B is a winner because more visitors achieved the goal; or it can inconclusive, where no statistically significant difference can be found among the test subjects. Even though the name is A/B testing, tests can have more than two variations. [24]

Eric Peterson reminds that when running A/B tests it is important to change only one variable at a time. He also discusses the importance of the process of diverting traffic. When testing, it is critical that visitor diverting is done in an accurate fashion. He suggests first test to be so-called null test: once everything is up and ready to test, first flow 50/50 traffic through the exact same pages. If the result is that the pages get nearly the same rates,

[5] Kaushik [29] notes that current reporting tools in web analytics software do not know how to compute statistical significance; instead, calculations have to be made in external software, like spreadsheet software.

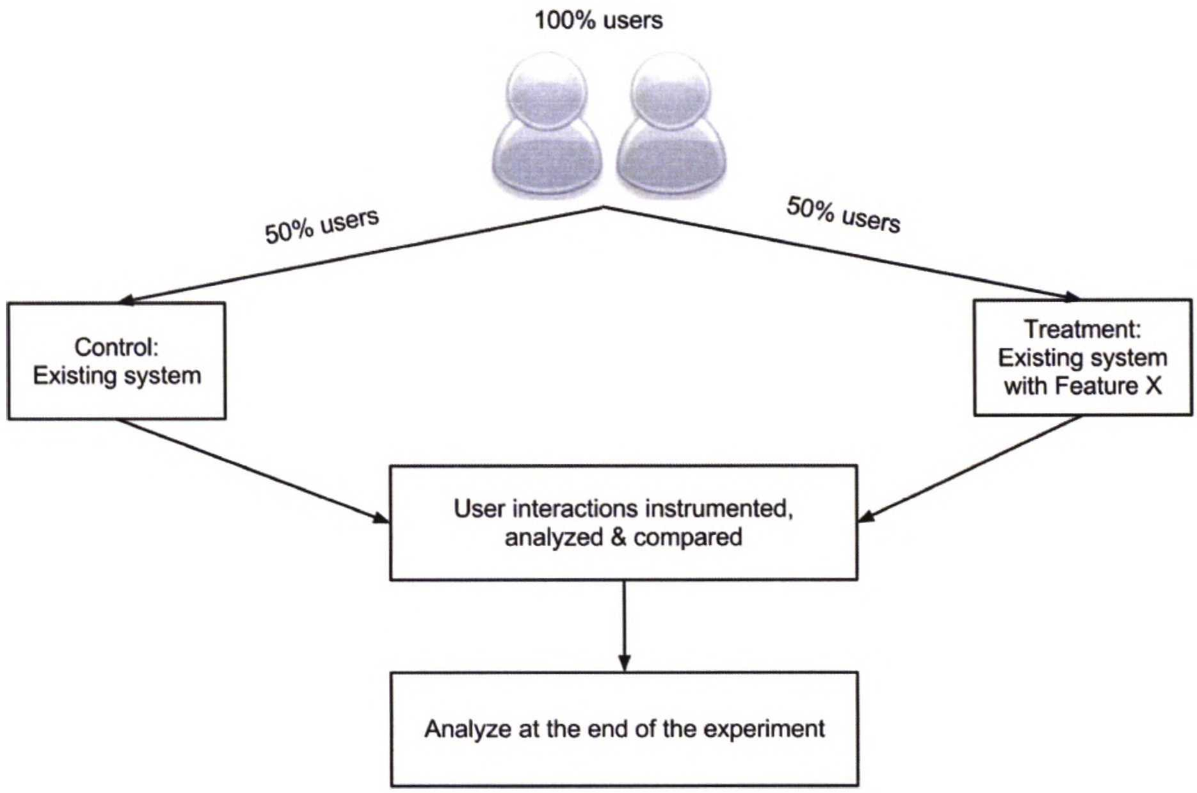

Figure 2.4: High-level flow for A/B test [32].

within 5 percent, the visitor diverting is done correctly. [45] When the tests are executed and it is time to decide based on data, Avinash [29] reminds not to aim for perfection, but instead to satisfy with 90% confidence. If you strive for perfection, nothing ever gets done, argues Avinash.

A study by Lindgaard et al. found out that visitors react very quickly to web pages. According to their study, it takes only 50 milliseconds to form an initial impression of the web design and that initial impression affects how much the visitors values the web page [37]. The finding stresses the importance of A/B testing on landing page optimization. Even small changes, like changing the picture, can have a big impact on web site performance.

Chapter 3

Methods

"If you can not measure it, you can not improve it."
— *Lord Kelvin*

This chapter introduces the research methods used for this thesis. First it tells about web site valuation framework, a model that we defined to estimate the value of a web site. Then, chapter tells about exploratory behavior analysis, traffic source analysis and A/B testing. Last section discusses about statistical significance and introduces the statistical test we used, G-test.

3.1 Web site valuation framework

Web site valuation can be defined to two subcategories. First is about valuing the web site by the amount of revenue it generates. There are many business models for web sites to generate revenue: advertising model, merchant model, subscription model and affiliate model to name a few [67]. Usually in B2B context the revenue is generated in e-commerce model or in sales lead generation. Second subcategory is about valuing the web site by the amount of cost savings it provides. A web site can reduce operational costs in multiple ways: automating processes or providing electronic versions of manuals, to name a few. For web site valuation, both subcategories have to be considered. The model presented in this section supports estimating a web site that is designed to produce sales leads.

For web site valuation the focus was practical. This model does not take into account the value in brand.

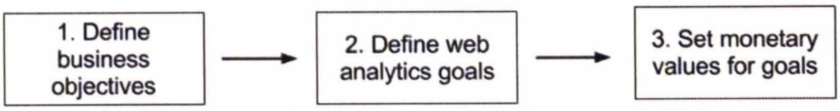

Figure 3.1: Website valuation model.

3.1.1 Revenue generation

For this thesis, a web site valuation model described in figure 3.1 was used. The valuation model was adapted from the recommendations of practitioners [11] [29]. The model contains three steps: 1) defining the general business objectives for web site; 2) generating web analytics goals from business objectives; and 3) setting monetary values for goals. As an example, a general business objective can be to sell products and therefore web site goals can include orders and brochure downloads. For web site valuation, we have to have a fully configured web analytics tool that is tracking web site usage. Web analytics tool is tracking web site usage to find out the number of times visitors behave so that the goal is fulfilled. That number is called *goal completions*. We will present two different methods to estimate a value to goal completion below.

In B2B web sites there exists typically two types of goals: 1) goals, that generate revenue in themselves, like an order from ecommerce site, and 2) goals, that are part of sales funnel but goal completion itself does not create revenue, like contact request or brochure downloads. The valuation for type 1 goals is trivial, the goal value can be defined as:

$$\textit{Goal value} = \textit{Goal completion value} \tag{3.1}$$

The valuation for type 2 goals is more complex. First, we have to know the probability that goal completion leads to a sales lead. This is an estimation that might be hard to base on factual numbers only. For example, in B2B context where company purchasing processes are generally long [29], it is hard to know how many brochures have to be distributed to generate one order. For some goals it is easy, a contact request is a sales lead itself, so the probability of goal completion turning to a sales lead for that goal is 100 %. Then, we have to know how often a sales lead generates an actual order. For this thesis, we have used a generic B2B context sale funnel estimation estimating that 1 % of sales leads becomes an order [50]. The Company is using the same estimation in their internal considerations. Finally, we have to know the average order value for company. With these three factors we have defined a formula for type 2 goal completions that estimates the goal value:

$$Goal\ value = P(Completion\ to\ Lead) * P(Lead\ to\ Order) * Average\ order\ value \tag{3.2}$$

Once we know the valuation of each goal completion that brings revenue we can estimate the total value of revenue that web site generates with following formula:

$$Total\ value\ of\ web\ site = \sum_{i=1}^{n} Goal\ value_i * Goal\ completions_i \tag{3.3}$$

Now, as we know the total revenue generated by web site, we can segment visitors to different segments and see their relative value. For example, now it possible to see if social media traffic is more valuable to Company than search engine traffic.

Now, as we know the total number of visits and total value of web site, we can calculate the value per visit. Value per visit metric is interesting in itself, and particularly useful when used with segmentation. It can be calculated with following formula:

$$Value\ per\ visit = \frac{\sum_{i=1}^{n} Goal\ value_i * Goal\ completions_i}{Number\ of\ visits} \tag{3.4}$$

It is also possible to calculate the value of a visitor, one needs only to change the number of visits with number of visitors in the formula mentioned above. Section 2.3.2 introduces the accuracy issues in web analytics. With the current state of technology identifying perfectly unique visitor is not possible without requiring visitors to register. For example, same person could use a work laptop to click an advertisement and end up in a web site, then use tablet device to browse that web site at lunch hour and then make the order with home desktop computer in the evening. The person would count as three visitors and mess up the visitor valuation. Visit valuation would still be valid. Therefore we think that estimating the value of a visitor is not viable, but estimating the value of a visit is.

3.1.2 Cost savings

For cost savings we use the same model as we used in revenue generation, defined in figure 3.1. The only difference is that monetary value of a goal is now a cost savings estimate, not revenue estimate. We present two different methods to estimate the cost saving value.

One type of reducing cost is automating a task that needs manual labor. Yearly salary for the person who would execute the manual labor is needed for goal value estimation. For example, before internet someone had to answer the questions about contact locations, like where a supplier in certain country is or what is a phone number to a sales office in certain city. Nowadays that information can be found online. A formula for estimating a cost saving of task automation is presented below:

$$Goal\ value = Manual\ labor\ needed\ (in\ minutes) * Yearly\ salary/200/7.5/60 \tag{3.5}$$

Another way to estimate cost is to compare it to the cost of producing same product or service in offline world. For example, a cost saving of a manual download online can be estimated by the value of a physical manual. One could argue that physical manual is more valuable than online manual so we added a factor to formula. On the other hand, downloading a brochure online is a conscious decision, receiving a brochure on mail is not which makes online counterpart more valuable. The factor defaults to 1, but it can be either more or less than 1. Formula is provided below:

$$Goal\ value = The\ cost\ of\ producing\ service\ offline * Factor \tag{3.6}$$

Formula above can also be applied to abstract goals, like job applications. There is a certain cost to receiving to job application offline, for example the cost of participating to a HR fair. In HR fair case, the cost of single job application would be calculated by dividing the cost of fair by the amount of received applications.

Like total revenue estimation, total cost savings can be estimated with following formula:

$$Total\ cost\ savings\ of\ web\ site = \sum_{i=1}^{n} Goal\ value_i * Goal\ completions_i \tag{3.7}$$

3.2 Exploratory behavior analysis

In exploratory behavior analysis we observe the visitor traffic from many different point of views. The purpose of exploratory behavior analysis is to find anomalies in behavior. These anomalies usually turn out to reveal something of use, and they are called *insights*. Typically insights support decisions and drive action, and therefore finding insights is one of the goals of web analytics [29].

In this thesis we observe the visitor behavior on Company web site from different point of views. One point of view is technology: browser, screen resolution and web site speed. Another point of view is country: we analyze how behavior varies between visitors from different countries. We also analyze the mobile and tablet usage and compare it to desktop usage and finally show the performance of key performance sections of the web site. Throughout traffic observations the valuation model introduced in section 3.1 is used to evaluate the monetary value of web site usage.

We utilize segmentation to further analyze behavior. Segmentation can be classified to three segmentation strategies. First is segmentation by source. It is critical to segment by source in order to measure the relational value of different traffic sources. Trivial use case would be to find out if campaign is successful. Second is segmentation by behavior. Visitor traffic should be segmented on the basis on how the visitors are communicating the web site. The third strategy of segmentation is segmentation by outcome - to find out if converted visitors behave differently to non-converted visitors. [27]

Statistically speaking, behavior analysis is simple. Most of the observed values are segmented averages. In some cases, distributions are analyzed. Google Analytics, the web analytics tool used in this thesis, does not provide tools for analyzing variation or medians. For key findings we have applied statistical significance testing.

3.3 Traffic source analysis

Web site visitors have three possible methods to enter the web site:

1. *Direct traffic*: visitor writes the web site address to browser address bar or selects the web site from bookmark.

2. *Referral traffic*: visitor follows a link that leads to the web site. Referral traffic can be further refined to *social media traffic*, referrals from social media sites, and to *other referral traffic*.

3. *Search traffic*: visitor uses search engine to enter the web site. Search traffic can be further refined to *organic traffic*, non-paid traffic, and to *paid traffic*, advertised traffic. It can also be refined to *brand traffic*, traffic from search engines that have a brand name in keywords, and

to *non-brand traffic*, traffic from search engines that does not contain brand name in keywords.

Plaza [47] monitored the effectiveness of traffic sources by finding out which traffic source produced most return visits. On this thesis, we take a step further in traffic source analysis: we compare different traffic sources by outcomes. First, we compare traffic sources by their conversion rate and then we compare traffic sources by the amount of value they generate.

3.4 A/B testing

During this thesis we used A/B testing to test out different design ideas. The goal was to improve the conversion rate of different site goals. A/B testing is introduced in section 2.7.

We used Google Analytics Content Experiments, a simple free tool for A/B testing, to run A/B tests. During testing we found out the tool to be too limited for certain tests. For those tests we used Google Analytics Content Experiments to divide traffic automatically to different variations, but instead of using same tool for analyzing results, we decided to set up custom events and use the custom events for finer analysis.

3.5 Statistical significance

In this thesis the results from A/B tests and traffic observations are subjected to statistical significance tests.

Usually in statistics it is not possible to measure the whole population; instead, statistical tests rely on sampling, measuring only a part of total population. Sampling introduces chance, sometimes called noise, to measurements. Therefore it is vital to evaluate the statistical significance of the results. Statistical significance means that the observed difference between two or more variations reflects a pattern rather than just chance. Statistical significance only tells that there is the difference, not that it is significant in magnitude. If the result is not statistically significant, conclusions should not be done based on that result. [40]

Confidence levels are used to evaluate the probability of chance. If confidence level is 95 %, then the probability that the observation is by chance is only 5 %. Typically used confidence levels are 95 %, 99 % and 99.9 % [22]. In A/B testing also 90 % confidence level is used [2]. There are some tracking accuracy issues in web usage tracking, as discussed in section 2.3.2.

Because of those accuracy issues, in A/B testing it might not be reasonable to try to achieve very high, like 99.9 %, confidence levels.

Statistical significance is evaluated by statistical tests. Statistical tests begin by forming a null hypothesis and alternate hypothesis. In A/B testing, the null hypothesis is that there was no difference between test subjects A and B. Next phase is to run the actual test, which usually gives a P value. P value is value between 0 and 1 that indicates the probability of observed results, assuming that null hypothesis is correct. If P value is low enough, like less than 0.05, we decide it is too unlikely that the observed values differ by chance only and we discard the null hypothesis and instead apply alternate hypothesis. In A/B testing the alternate hypothesis is that there is a difference between test subjects A and B.

3.5.1 G-test

There exist many different statistical tests for different purposes with different presumptions. As mentioned in chapter 2.4.2.1, most web metric values are either long-tail distributed or randomly distributed. Therefore typically used statistical tests, like Z-test, cannot be used because they assume that the results are divided according to normal distribution. [40]

We have used G-test for both A/B testing and for traffic observations. G-test does not assume that results are normally distributed [40]. G-test for independence is used to measure the statistical significance of two nominal variables. Nominal variable is non-numerical variable, like sex: possible values are male and female. A/B testing tests conversions where individual visits have two possible values: converted and non-converted. There is multiple online calculators (like [12]) to easily calculate the probabilities with G test. The general form of G test goes as follows: [40]

$$G = 2\sum_{i} O_i * ln(O_i/E_i)$$

The O in formula above is observed result, and E is expected result. Expected result is sometimes called "Control" in A/B testing. The formula gives G value, where statistical significance can be derived.

Chapter 4

Environment

This section presents the Company, for which the thesis was written. It also introduces the Company web site, web site goals, metrics and related valuation in addition to introducing web analytics tool and the technology behind web site. Then it discusses about web usage data and introduces refined research questions.

4.1 Company

The Company that is researched is a large, Finland-based global manufacturing company that has sales and service operations in nearly 90 countries and operates in business-to-business sector (B2B). The Company is public and it is listed to Helsinki Stock Exchange. In addition to manufacturing, it also provides services like maintenance and training for product owners. The Company has 28 subsidiaries in five continents.

The Company has recently invested in building a new, modern web site.

4.2 Web site

The company has a large web site that serves customers in 10 different languages and contains information of dozens of subsidiaries. It has thousands of content pages and thousands of files available for download. The business model for the web site is manufacturer model meaning that Company can reach buyers directly [67]. From the revenue viewpoint the main goal of the web site is to generate sales leads.

The new web site was launched in late 2012. Web site has a responsive design - it has three different layouts: one for desktop, one for tablet and one for mobile.

Before, on the old site, the use of web analytics tools was very limited - only the most basic features were used. For this thesis the use of analytics was developed further. Many new features were developed to customize the use of web usage tracking. More than twenty customized tracking events were developed for new web site to fully understand the site usage.

The web site gets visited thousands of times each day.

4.2.1 Technology

The web site was developed on top of Swedish content-management-system EPiServer [13]. EPiServer uses Microsot's .NET framework and ASP.NET Web Forms technology. The site is heavily customized, EPiServer's out-of-the-box features were not enough for the Company. On the front-end, the site uses heavily JavaScript and AJAX to provide rich and responsive user experience. The site uses HTML5 Boilerplate and Twitter Bootstrap to provide responsive design.

4.2.2 Analytics tracking

The Company has been using Google Analytics (GA) as their tracking solution in the old web site, so they chose to continue to use GA. This section describes briefly the features of GA and then describes how the web site takes advantage of them.

4.2.2.1 Web analytics tool: Google Analytics

Google Analytics is a free, software-as-a-service web analytics solution from Google. The basic service is free of charge. GA is currently the market leader in web analytics. The sources indicate Google Analytics' market share to be somewhere between 40% and 90% whereas the second most used analytics tracking software's market share is between 7% and 15% [7, 9, 38]. GA is therefore dominating the market on most sectors. GA has been widely used in academia thus making it a feasible option for thesis [21, 44, 48, 66].

GA uses page tagging methodology to collect clickstream data. It requires few lines of JavaScript, *a snippet*, to be included to every page of the web site.

GA provides the basic functionalities of web tracking software including all the standard metrics as discussed in chapter 2.4.2. In addition the software is customizable and extendable. It has built-in support for custom events, goal and conversion rate tracking, custom variables which can be used to segment visitors, funnels and social media plugins. Customization support is important, as usually most important insights are heavily dependent on the site so the site's tracking should be heavily customized as well.

GA tracks page loads by default as long as the tracking snippet is in place. Custom events are intended for tracking events that happen without page loads, for example "user starts to play video" is an example of an event. Typically AJAX requests are good places for custom events.

Goals are the customizable actions that web site owners want site visitors to do. They can be, for example, a purchase on an e-commerce web site or a contact request from B2B web site. In GA goals can be either threshold-type goals or traditional goals. Threshold-type goals trigger when some threshold value is crossed: for example, visitor has spent more than 15 minutes on the web site or that visitor has visited 10 different pages. Traditional goals trigger when event happens. Event can be custom event or page load to specified URL.

Custom variables are used for advanced segmenting and they can "tag" visitors. Custom variables have three levels: page level, session level and visitor level. Page level custom variable follows visitor's actions during a single page view. It is useful when events from one page should be grouped together. Session level custom variable follows visitor during single visit to web site. It can be used, for example, to track the effectiveness of marketing campaigns. A campaign-specific session level custom variable allows analysts to track and compare user behavior in different campaigns. Visitor level custom variable is most advanced type of custom variable: it tracks same visitor between multiple visits. It can track if visitors that visit site more than once behave differently. It can also be used for tracking how many visits it takes, on average, before visitor converts.

Funnels are clearly defined processes that advance from first step to last step. They can be used with goal tracking, as long as the goal's target is URL. GA does not support funnels for goals with events. GA also supports social media interactions tracking with plugins.

4.2.2.2 Description of customizations

The web site was configured to support tailored usage tracking. The web site takes advantage of custom events, custom variables and social media plugins. Four custom variables, more than twenty custom events and social media tracking for each social media provider that Company uses were configured. Web site was also customized to support internal site search tracking. To get conversion tracking, we defined multiple web site goals.

Several GA profiles were created for different purposes: one unfiltered, one general-purpose filtered, one for revenue generation estimations, one for cost savings estimations, one for A/B testing and one for each stakeholder group. Each profile has its own goals and dashboards.

4.2.3 Metrics

We have used multiple web metrics to analyze the web site usage. In addition to the standard metrics introduced in section 2.4.2 we have defined and applied five custom metrics. This section explains the customized metrics.

Visits / day metric shows the amount of visits in a day compared to visits in a week. This is used to compare the visits per day in weekend to visits per day in weekdays. For weekdays, it is calculated by dividing total weekday visitors by five and then by total weekly visitors. For weekends it is calculated by dividing total weekend visitors by two and then by total weekly visitors. The unit is percentages.

% of value metric shows the amount of value generated compared to total value generated. This metric is useful for visitor segments. It is calculated by dividing the total value of segment by the total value of the web site. Total value of the web site is calculated with formula 3.3. The unit is percentages.

Value per visit metric shows the value of a single visit. It is calculated with formula 3.4. The unit is euros.

We have also used *Micro Conversion Rate* and *Macro Conversion Rate* metrics. The former tells the conversion rate for micro goals and latter tells the conversion rate for macro goals.

4.2.4 Web site goals

We have defined eight goals for Company web site. We have followed Kaushik's [29] advice and divided goals to most important goals, macro goals that lead to *macro-conversions*, and to less important goals, micro goals that lead to *micro-conversions*. Table 4.1 lists micro and macro conversion goals.

Table 4.1: Micro and macro conversion goals

Macro goals	Micro goals
Submit a contact request	Download a brochure
Register to training	Download a support file (manual, software etc.)
	Download a media file
	View reference story
	View contact details on contact map
	Submit a job application

4.2.5 Web site goal valuation

We have used the web site valuation model presented in chapter 3.1. For this thesis, we identified five revenue generating goals and six cost saving goals. It is important to note that some goals introduced in previous section belong to both to revenue generating goals and to cost saving goals. The estimations done during this thesis are rough, especially for cost-savings, and they are likely to change to more accurate values, should Company choose to continue developing current tracking system.

Table 4.2 presents one type 1 revenue-generating goal, goal that provides revenue by completion, and four type 2 revenue-generating goals, goals that increase the likelihood of an order, for Company web site. Table describes the goal, the probability that goal completion leads to sales lead, the probability that sales lead advances to order, average order value and, finally, the valuation for goal. Training registration is type 1 goal, so the value estimation is trivial (formula 3.1). For other goals, the valuation formula 3.2 was applied. For example, we estimate that one out of hundred brochure downloaders become sales leads for Company. Out of those, we estimate that 1 % actually places the order [50]. Average order value is 5500 €. With these values, we can estimate the value of a single brochure download: 0.55 €.

Table 4.2: Revenue generating goals for Company web site.

Goal	**P(Completion to lead)**	**P(Lead to order)**	**Average order value**	**Goal value**
Download a brochure	0.01	0.01	5500 €	0.55 €
View reference story	0.01	0.01	5500 €	0.55 €
Contact request	1	0.01	5500 €	55 €
Contact details query	0.2	0.01	5500 €	11 €
Training registration				Training fee, 500 €- 1000 €

Table 4.3 introduces the cost-saving goals for Company web site. Table lists two labor-saving goals and four offline cost -saving goals. The labor saving goals, software download and contact details query, have been estimated with formula 3.5. The annual salary of an engineer who would manually send out software, is 60 000 €. The annual salary for salesman who would answer to contact details query is 80 000 €.

The offline cost type goals have been estimated with formula 3.6. We have used a factor of 0.5 for brochures, PR files and manuals. Factor 0.5 means that we estimate that the value of physical products, like manuals, is double compared to their online counterparts. For job application, we used a factor 1, because we think a job application online is as valuable as job application offline.

Table 4.3: Cost-saving goals for Company web site.

Goal	Salary	Time required	Offline cost	Factor	Value
Software download	60 000 €	15 mins			10 €
Contact details query	80 000 €	15 mins			13 €
Job application			20 €	1	20 €
Brochure download			1.5 €	0.5	0.75 €
PR file download			2 €	0.5	1 €
Manual download			2 €	0.5	1 €

We have defined custom analytics for corporate web site, defined multiple goals and we have also valued the goals. Now Company web usage tracking software Google Analytics is constantly monitoring the revenue and cost savings that web site generates.

4.3 Web usage data

The analytics data for custom metrics that were defined as a part of this thesis, has been tracked since February 2013. The collection of web usage data continued until the finish of this thesis in May 2013. Data for non-custom metrics have been collected since the new site launch in October 2012 and since 2010 for the old web site. The old web site used older version of GA snippet and therefore it collected less information than the new snippet. As the web site gets visited thousands of times each day, the necessary data for statistically significant results is easily available.

During the thesis we were only interested in external web site users. External in this context means users that are not Company employees. Even though there is value for internal use of Company web site, like information sharing and support file downloads, that value was not evaluated in this thesis. For this thesis, external users have the possibility to become sales leads and training registrars and that was a major focus. Therefore a GA profile with multiple filters was used for traffic observations to filter out Company employees. As discussed in section 2.3.2 it is impossible to perfectly filter non-desired visitors. However, according to statistics of referrals from Company intranet site we estimate that over 90 percent of internal desktop users were filtered away. Because people do not necessarily use Company's internet connection to browse internet in mobile devices, we could not filter out Company employees' mobile visits. Apart from the fact that those visits do exist, we cannot estimate their volume.

4.4 Refined research questions

Now, after literary review and after becoming familiar with the environment and with the methods available for web analytics, we can refine the original, intentionally very broad research questions introduced in section 1.3. The following list specifies more accurate research questions.

1. How to study web site behavior using web analytics?
   (a) Is localization on Company web site effective?
   (b) Does speed affect conversions?
   (c) Is responsive web site version performing well?
   (d) What sections of the site perform best?
   (e) Which traffic sources perform the best?
   (f) Do web usage data justify made technology choices?
   (g) Do visitors to Company web site visit the site only in weekdays?
   (h) Is the new web site performing better than the old web site?
2. How to improve web site performance using web analytics?
   (a) Can A/B testing be used to improve Company web site performance?
3. Can web analytics be used to measure B2B web site's commercial value?

From these research questions we have formulated ten hypotheses. These hypotheses will be tested in chapter 5. Section 7.1 accepts or rejects hypotheses and also discusses their generalization potential. The following list shows hypotheses and also tells that which hypothesis corresponds to which research questions.

1. Visitors convert more in their local language (1a)
2. Visitors bounce less in their local language (1a)

3. Visitors convert more when site is faster (1b)
4. Providing responsive design to mobile visitors is important (1c)
5. Web analytics can be used to support decisions (1d, 1e)
6. Usage data justifies technology choices for Company web site (1f)
7. B2B visitors visit the site mostly in weekdays (1g)
8. New Company web site outperforms old web site (1h)
9. Small web page design changes can change visitor behavior (2a)
10. B2B web site's commercial value can be measured (3)

Chapter 5

Results

This chapter tells the results of the study. The Company web site is observed as a case study. First, the chapter tells exploratory behavior observations, then results from traffic sources and finally it presents the results from A/B tests.

5.1 Exploratory behavior observations

This section tells the exploratory behavior observations from many different viewpoints. First, we compare old Company web site to new site, then we discuss about technology choices from browsers to resolutions and to website speeds and then we move to presenting the results from regional differences. Then, mobile visitor usage is analyzed and finally, site sections' performance is compared.

5.1.1 Comparing old site to new site

In this subsection we compare the old web site's performance to the new site's performance. The new site was launched late 2012. It is not possible to make perfect comparison between two sites, because on the old site the analytics was not as developed as on the new site. Old site had old GA snippet so no speed statistics are available. Old web site also lacks custom events and goals. Therefore, no downloads, no amount of job applications or conversion rates can be compared. Luckily we were able to compare one goal, contact requests, because we could get the statistics from Customer's CRM system. On old site there were no filters to filter away the visits from Company employees. To make the comparison more fair, company employee filters were not applied for new web site either. Because old site tracked

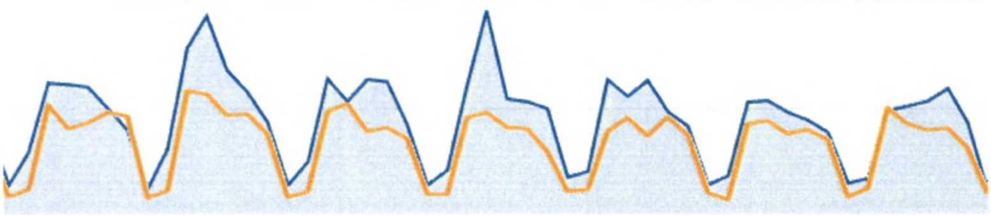

Figure 5.1: 7-week time series of visits comparing old web site (orange) to new web site (blue).

visitors differently to new site, for visits and visitors metrics only Finnish language was selected. For other metrics, all available data was used.

Figure 5.1 shows the daily visits to Company web site during 7-week period. Orange line indicates old web site and blue line indicates new website. On graph we can see the weekly circulation of visits. Mondays and Tuesdays are the most popular days while other weekdays have only slightly less traffic. Weekends have clearly less visits. Graph shows two insights: that there were no changes in weekly trend after introducing new website; and, that new web site outperforms old web site in terms of visits.

Table 5.1: Comparing key web metrics in old and new site

Metric	**Old site**	**New site**	**Change**
Visits	15 300	18 082	+18 %
Visitors	10 721	12 711	+19 %
Pages / Visit	3,94	3,32	-16 %
Avg. Visit duration	03:09	04:10	+32 %
Bounce Rate	41%	37%	-11 %
Contact Requests	120	240	+100 %

The table 5.1 shows some key metrics for the new and for the old website. The values in the table were collected during five months period, 10 weeks for each site. Values show that new web site clearly outperforms old website: visits and visitors are up 19 percent, contact requests are up by 100 percent, average visit duration is up by 30 percent and bounce rate has been lowered by 10 percent to 37 percent. To compare, average bounce rate is 37 percent according to Katie White from Blizzard Internet Marketing [63]. Only pages per visit metric is negative, showing 15 percent decline. Pages per visit is usually used as an engagement metric: more pages per visit, more engagement. In this case the negative pages per visit metric can be positive: the new site is more focused, visitors find what they are looking for faster than before. It is impossible to know for sure if it is negative or positive without qualitative data, such as a survey.

5.1.2 Technology

This subsection introduces the traffic observations from technology perspective. First it leads the reader through browser observations, discusses about the usage share of browsers and shows some key trends in browser usage share. Then it discusses about screen resolution, its effect on web site effectiveness, shows observed screen heights and widths of Company web site visitors and finally presents web site speed results.

5.1.2.1 Browser

The Company web site supports only modern browsers. Support for browsers that does not comply to standards in HTML, CSS and JavaScript, notably Internet Explorer versions 6 and 7, was dropped during the development. Because of that decision it is important to understand the browsers visitors are using to browse the Company website.

Figure 5.2 shows the usage share of browsers in the Company website and compares it to global browser market share. The figure is constructed as time series from 2010 to 2013. The observed trends in Company web site are the same as the trends in global marketshare, tracked by StatCounter [58]. Internet Explorer has been losing market share significantly, while Google Chrome's share has been rising rapidly. Firefox has been on slight decrease, and Safari on slight increase. However, there are differences in absolute values. In 2013, StatCounter shows that Chrome is market leader with 38 percent market share, and Internet Explorer is follower with 30 percent market share. Company web site is B2B website. Companies have been traditionally using Internet Explorer as the default browser so the emphasis on Internet Explorer on Company web site is expected.

Most browsers, like Safari, Firefox, Chrome and Opera follow W3C's standards on rendering HTML and CSS. Internet Explorer has not been following standards in the past, especially Internet Explorer 6.0 is notorious for its poor standard-compliance. However, the situation has changed - Internet Explorer has supported standards fairly well since version 8.0. For these reasons, it is important to see the usage share of different Internet Explorer versions. The figure 5.3 shows the usage share of different Internet Explorer versions for Company website. The figure shows that versions 6.0 and 7.0 are

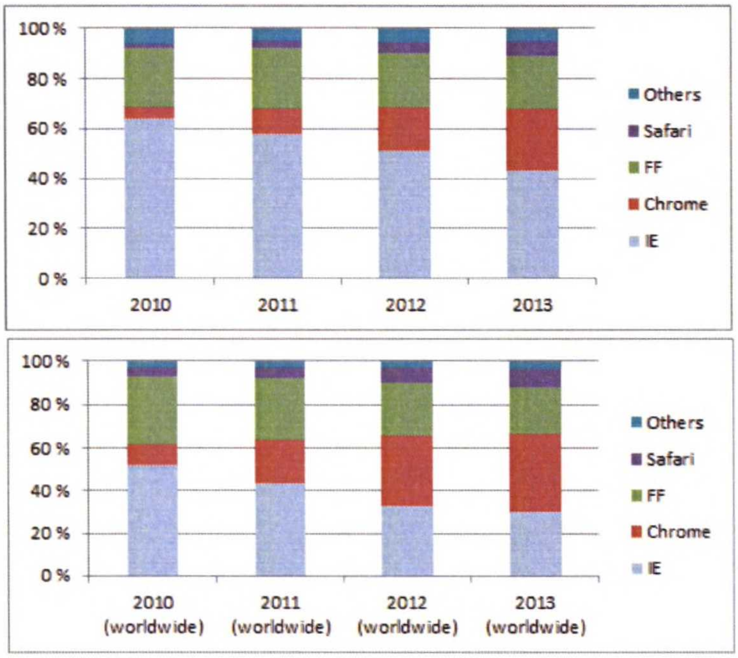

Figure 5.2: Time-series showing browser usage share of browsers on a global scale and on Company website.

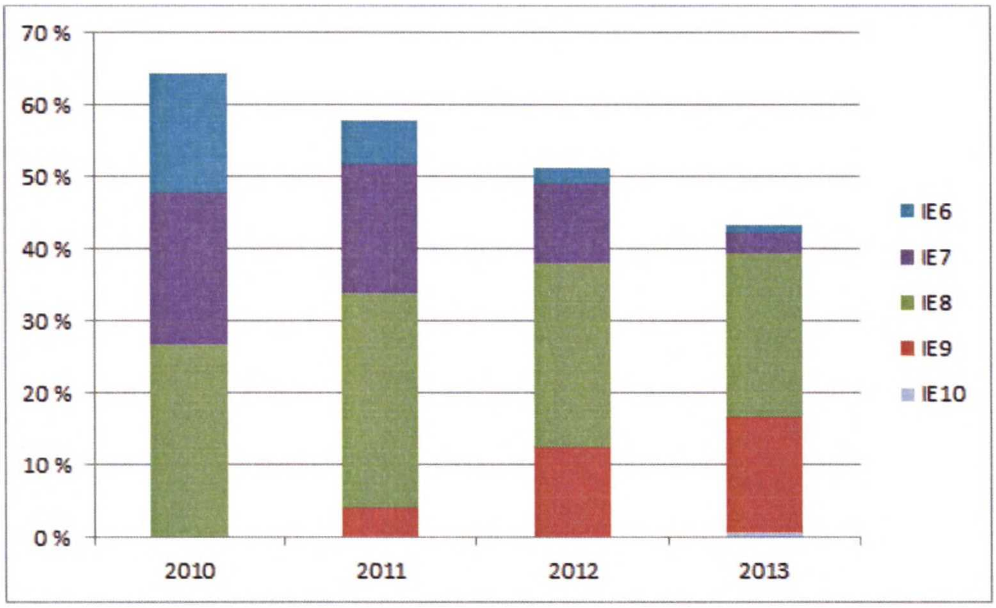

Figure 5.3: Time-series showing usage share of different Internet Explorer versions on Company website.

becoming a rarity; in 2013, only less than 3 percent used them. And, more importantly, the usage share for these browsers has been declining rapidly.

5.1.2.2 Screen Resolution

It is important for web site visitors to be able to see the most important parts of the site, such as calls to action, on the site without scrolling. It has been shown that requiring users to scroll drives conversion rate down [36] [65]. Company website's desktop version was designed for modern, large monitors. Table 5.2 shows some key points in terms of resolution in page design. On height, the first 300 pixels is reserved for header, header picture and main menu. Quick contact form, which is togglable on every page, requires 750 pixels to be fully visible without scrolling. The web site changes to mobile responsive layout when screen width is below 360 pixels, and to tablet responsive layout when screen width is less than 980 pixels.

Axis	Threshold	Description
Height	300 pixels	The start of main content area
Height	400 pixels	Main title fully visible
Height	750 pixels	Quick contact form fully visible
Height	860 pixels	Body text visible on product page
Width	360 pixels	Switch to mobile responsive design
Width	980 pixels	Switch to tablet responsive design

Table 5.2: Some key thresholds in visual page design.

The easy days of supporting only a handful of most popular resolutions are gone. Since the site launch there have been visits to Company web site with more than 1300 different screen resolutions. The variation of resolutions is vast, top ten resolutions accounted for only 80 percent of visits. Figures 5.4 and 5.5 show cumulative histograms of web site visitor's screen widths and screen heights. Figures show only visits from desktop users, the visits from mobile and tablet visitors is filtered away. Mobile resolution analysis was omitted, because the variety in screen sizes is vast. Fine-tuning mobile experience requires tuning the web site to multiple different handheld devices and therefore it requires significant amount of time to develop. Also, only less than 1 out of ten of web site visitors are mobile visitors.

The figures show that half of the web site visitors have a screen height of 900 pixels or more. 35 percent have less than 800 pixels of height in screen resolution. Only five percent has more than 1100 pixels on height. On screen widths, 60 percent has 1300 pixels or more. Around 15 percent has a full HD monitor or larger, as their screen width is more than 1900 pixels. It seems

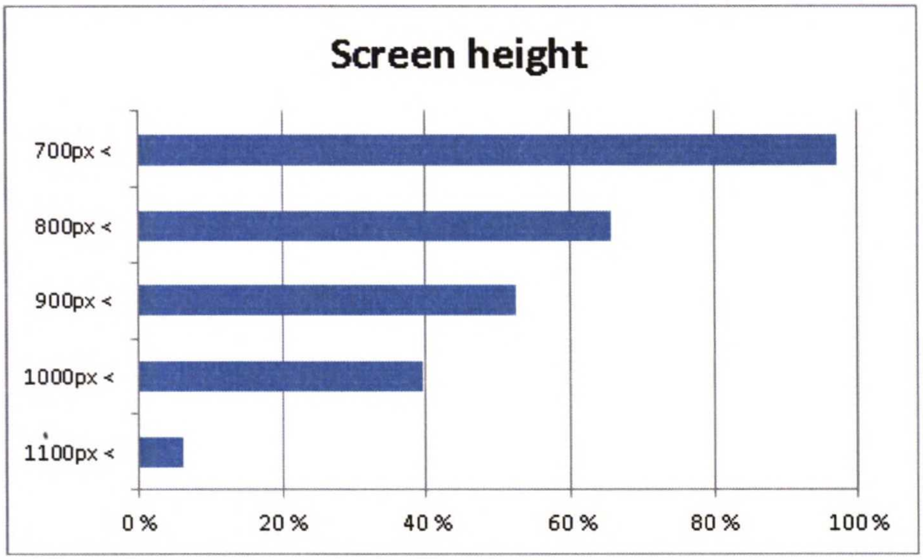

Figure 5.4: A cumulative histogram of screen heights of web site desktop visitors.

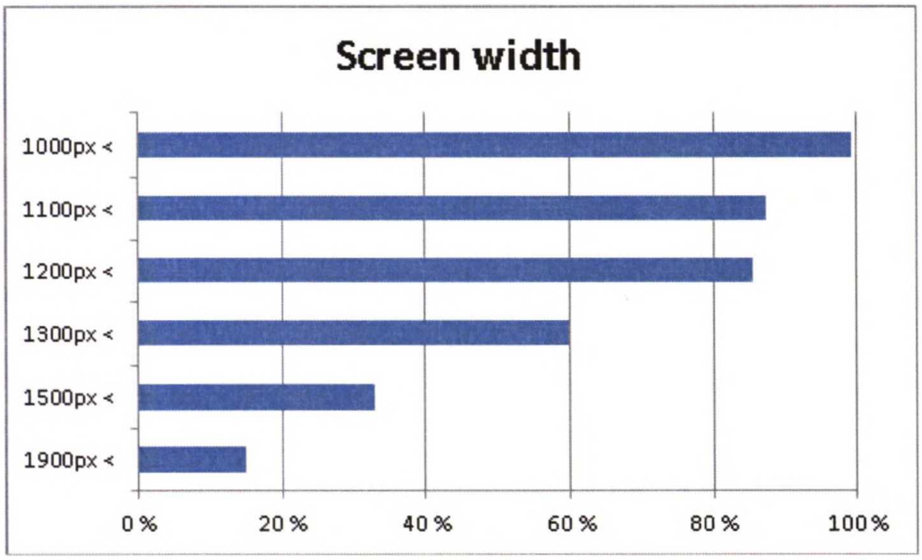

Figure 5.5: A cumulative histogram of screen widths of web site desktop visitors.

that today most monitors are wide-screen monitors, as screen heights are relatively low and widths are relatively high. The most popular resolution is 1366x768 with 18 percent of visits.

Resolution observations show that there is no problem with width. Desktop site is designed for 980 pixels, and 98 percent has a resolution that has a width of 1000 pixels or more. However, the site would look better with 1000 pixels wide screen if tablet's responsive design was applied instead of desktop responsive design. At the moment 10 percent of visitors have a screen width less than 1100 pixels and therefore suffer from poor visual experience. The height side is more problematic. 35 percent of site visitors have screen height of less than 800 pixels. That means that the site header takes almost half of the space and main title is at vertically at the center of screen. Also, body text is not visible at all on product pages without scrolling for these visitors. The site was clearly designed with larger screen resolution in mind. 40 percent of visitors have a screen height of 1000 pixels or more, and with that height the site functions ideally.

5.1.2.3 Web site speed considerations

Figures 5.6 and 5.7 show the effect of speed to bounces and conversions, respectively. Figures show distributions with different page loading times. For each page loading time bucket it presents two values: the amount of visits that bounced / converted that belong to that bucket - and the amount of visits that did not bounce / convert. The distributions show that on small page load times visitors convert more and bounce less – which is wanted behavior, whereas with large page load times visitors convert less and bounce more – non-wanted behavior. The threshold for Company web site seems to be at seven seconds: below that behavior metrics are positive, above it behavior metrics are negative.

Unfortunately GA presents only aggregate data. Therefore it is not possible to get speed values as raw data to calculate standard deviation. It also does not provide standard deviation as itself, so we could not calculate statistical significance tests for the effect speed has to bounces and conversions. We can only conclude that behavior in Company web site indicates that smaller loading speeds improve conversions and decrease bounces, which is in line with previous studies [11, 30].

Page Load Time Bucket (sec)	Percentage of total
0 - 1	
Non-bounce Visits	**2.61%**
Bounce Visits	**0.11%**
1 - 3	
Non-bounce Visits	**28.25%**
Bounce Visits	**4.47%**
3 - 7	
Non-bounce Visits	**41.74%**
Bounce Visits	**35.79%**
7 - 13	
Non-bounce Visits	**15.29%**
Bounce Visits	**26.50%**
13 - 21	
Non-bounce Visits	**6.18%**
Bounce Visits	**14.33%**
21 - 35	
Non-bounce Visits	**3.33%**
Bounce Visits	**9.68%**
35 - 60	
Non-bounce Visits	**1.63%**
Bounce Visits	**5.83%**
60+	
Non-bounce Visits	**0.97%**
Bounce Visits	**3.28%**

Figure 5.6: Distribution showing the effect of speed to bounces.

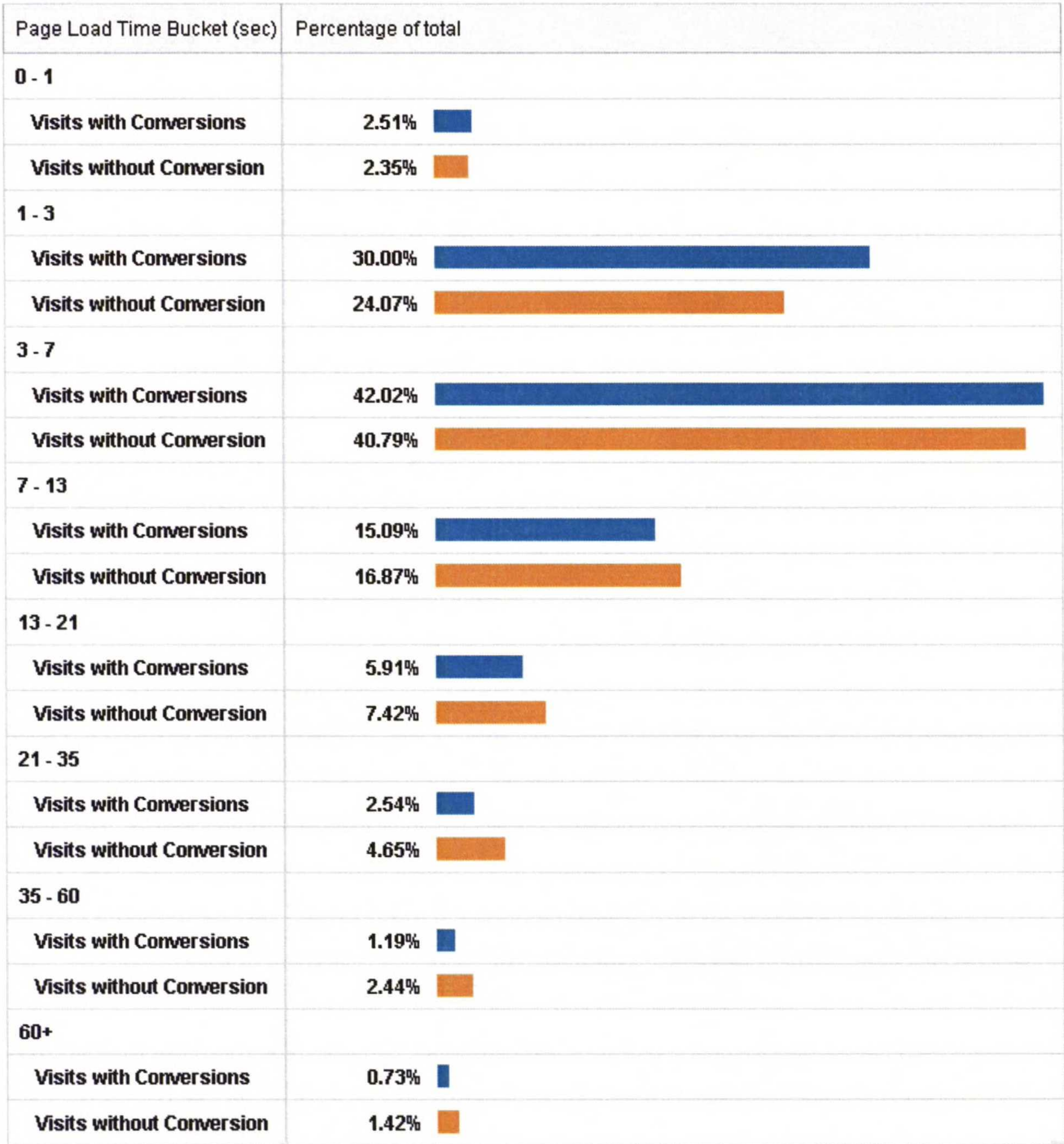

Figure 5.7: Distribution showing the effect of speed to conversions.

Table 5.3: Average web site speeds segmented by devices and continents and divided by different load segments.

Continent	Desktop load time	Desktop render time	Tablet load time	Tablet render time	Mobile load time	Mobile render time
Europe	0.6 s	4.4 s	0.9 s	11.5 s	1.2 s	12.8 s
North America	0.8 s	6.5 s	1.6 s	15.0 s	2.0 s	17.7 s
South America	1.6 s	10.5 s				
Asia	2.2 s	15.5 s				
Africa	1.4 s	36.3 s				
Global	0.9 s	6.2 s	1.02 s	11.9 s	1.3 s	13.5 s
Global (cached)	1.2 s	4.3 s				

Table 5.3 shows more web site speed observations. The average loading times are segmented by continents to get more meaningful results. All values presented in the table are averages. Load time is the time needed to load the HTML page from server. Render time contains everything after that: the loading of related assets (images, CSS and JavaScript files), manipulating DOM with JavaScript, loading external social media widgets and rendering the page.

Calculating web site itself slows down site so GA uses sampling to select only part of visitors for web site speed calculations. By default the sample rate is set to 1%, but during the thesis it was adjusted to 100%. Google recommends adjusting it to more than 1% with sites with relatively low traffic, like less than 100 000 daily visitors [2]. However, even with 100% sampling we were not able to get enough visitors for calculations - some values in table are empty because not enough samples were collected. For example, Africa's mobile and tablet values are empty. It strongly indicates that the usage of mobiles and tablets to browse the internet is very poor in Africa.

The web site loading times vary from 0.6 seconds in Europe to 2.2 seconds in Asia. The Company web server is based in Finland. As one could expect, results clearly show that the further away the visitor is from Finland, the larger the load times. In addition to the distance from web server the speed of local internet connection also affects the load times. Internet connections are generally faster in western countries than in developing countries. Still, an average load time of 2.2 seconds in Asia, especially compared to 0.6 seconds in Europe, is a bit high. Distributing the web site servers worldwide, for example by using content delivery network (CDN) would decrease the loading times.

The web site render times have a massive variation, from 4 seconds to as high as 36 seconds. The Company web site utilizes newest technologies, like web fonts and CSS3 transparencies and relies heavily on JavaScript and related libraries, like jQuery. These give web site a fresh and modern look, but they are also computationally expensive for computer to render. We can clearly see from the results that the site is slower in developing countries, most likely because the computers are slower there than in western countries. For example, the average render time is only 2.5 seconds in Norway and 20 seconds in Taiwan. It is to be noted that the site is faster than the numbers themselves show. The web site is usable and most of the content is visible already after 50-70% of the render time. The remaining time is used to modify DOM for top menu and for loading scripts that define functionality, not layout.

5.1.3 Regional differences

This section presents results for web usage, subsidiary pages and localization. The results are segmented by countries. The main objective of this section is to find out whether there is regional differences on Company web site usage and what kind of differences there is.

5.1.3.1 Web usage

The table 5.4 shows the differences in visits, bounce rate and conversion rate in weekends and weekdays for selected countries. It also shows the amount of mobile and tablet visitors. The top 10 visited countries were selected for comparison. Weekday visits are calculated as five days from Monday to Friday and weekend visits are calculate from Saturday to Sunday. India is practicing six-day working week [10] and that has been taken into account for the table.

Table 5.4: Web usage in March 2013.

Country	Visits /day [1]	Visits /day [2]	Bounce Rate [1]	Bounce Rate [2]	Conversion Rate [1]	Conversion Rate [2]	Mobile	Tablet
Finland	17,1%	7,1%	32%	32%	17%	13%	8,3%	3,3%
USA	17,4%	6,5%	34%	51%	26%	13%	7,7%	2,5%
China	16,6%	8,6%	37%	36%	15%	11%	2,5%	0,9%
Germany	18,5%	3,9%	22%	35%	32%	32%	3,8%	1,2%
Sweden	18,5%	3,8%	24%	25%	30%	21%	7,8%	0,9%
India	14,4%	13,6%	41%	34%	17%	18%	3,6%	1,0%
Italy	17,6%	6,0%	23%	32%	38%	21%	5,2%	1,8%
UK	18,3%	4,1%	27%	46%	29%	17%	8,0%	2,2%
Netherlands	17,8%	5,5%	27%	20%	40%	46%	7,7%	3,8%
Russia	18,2%	4,6%	35%	49%	18%	21%	2,0%	0,4%
Average	17,8%	5,4%	31%	38%	26%	19%	6,3%	2,1%

Results show that the conversion rates are better and bounce rates are lower for weekdays compared to weekends. That is expected, because Company operates on B2B sector. Also, most of the visits happen in weekdays: on average, weekdays have three times the daily visitors weekends have. European countries Germany, Sweden and United Kingdom have more than four times the daily visitors in weekdays compared to weekends. However, there is one exception: India produces practically as many daily visits in weekends as in weekdays. That is particularly interesting, as previous studies have shown that most of the traffic happens in weekdays [18]. That study, however, was limited to study only American citizens. This thesis has a web site that is visited on a global scale. Figure 5.8 visualizes the differences in web usage between countries in weekdays and in weekends.

Table also shows that there is large variations between countries in web usage. European countries, like Netherlands, Sweden and Germany have below average bounce rates and above average conversion rates. Values for Finland are somewhat flawed, because Finland has a large number of Company employee visits that we were not able to filter. Asian countries, on the other hand, have above average bounce rates and below average conversion rates. For example, India, China and Russia have all below 20 % conversion rate in weekdays and Germany, Netherlands and Italy have all above 30 % conversion rates.

[1] In business days
[2] In weekends

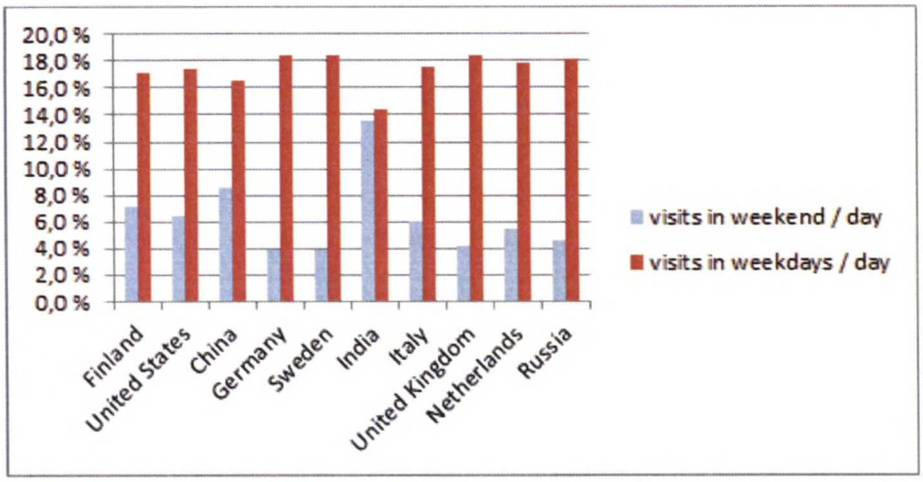

Figure 5.8: Comparing visits in weekdays to visits in weekdays for some countries.

The results show that even though Company operates in B2B sector, the web site gets visited in weekends as well and we should not filter out the weekend visits.

5.1.3.2 Localization and subsidiary pages

Company web site is translated in 10 languages and it contains information about 28 subsidiaries from five continents. Table 5.5 displays information about localization, its usage and effectiveness and the usage of subsidiary pages. The table shows the amount of visits each country generates and the percentage of visitors that visit subsidiary page. It also shows the percentage of visitors that use localization in addition to showing conversion rates and bounce rates for visitors that use localization and compares it to visitors that do not use localization. The official language for countries was selected for local language. For multilingual countries we have selected the most popular language as "local" language. For example, Finnish was selected for Finland, Holland for Belgium and Germany for Switzerland. The table shows 30 most visited countries. However, not all countries that have subsidiary belong in 30 most visited countries. Those countries, Mexico and Kazakhstan were added to the bottom of the list. Visits by countries is typical long-tail distribution: the 32 countries listed in table account only for 88 percent of all web site visits.

Table 5.5: Localization and subsidiaries

Rank	Country	% of visitors	Used local lang.	Conversion Rate	Bounce Rate	Local lang. Conversion Rate	Local lang. Bounce Rate	Visited subsidiary
1	Finland	20.6%	61%	17%	33%	20%	24%	1%
2	United States	10.7%	91%	24%	36%	25%	34%	10%
3	China	7.8%	74%	16%	36%	18%	35%	7%
4	Germany	5.6%	60%	31%	23%	46%	21%	5%
5	India	4.4%	–	17%	40%	–	–	21%
6	Italy	4.0%	69%	33%	26%	42%	25%	10%
7	Sweden	3.5%	–	29%	24%	–	–	68%
8	UK	3.0%	94%	28%	30%	28%	30%	4%
9	Netherlands	3.0%	66%	41%	26%	46%	20%	5%
10	Russia	2.4%	74%	19%	36%	19%	37%	2%
11	Brazil	2.0%	65%	27%	37%	31%	32%	8%
12	Canada	1.9%	96%	30%	33%	31%	32%	17%
13	Spain	1.9%	73%	32%	27%	30%	25%	4%
14	France	1.7%	61%	38%	29%	50%	33%	5%
15	Australia	1.6%	98%	40%	28%	40%	32%	16%
16	Austria	1.5%	54%	33%	22%	94%	27%	58%
17	Czech Republic	1.4%	–	13%	31%	–	–	77%
18	Norway	1.2%	–	32%	27%	–	–	66%
19	Denmark	1.2%	–	38%	22%	–	–	42%
20	Belgium	0.8%	38%	38%	23%	63%	14%	25%
21	South Korea	0.8%	–	31%	31%	–	–	12%
22	Switzerland	0.8%	33%	36%	27%	60%	27%	–
23	Turkey	0.8%	–	35%	27%	–	–	–
24	Ukraine	0.6%	56%	14%	44%	23%	45%	29%
25	Poland	0.5%	–	37%	30%	–	–	–
26	Romania	0.5%	–	36%	21%	–	–	19%
27	Slovakia	0.5%	–	20%	29%	–	–	8%
28	Thailand	0.5%	–	30%	35%	–	–	19%
29	Taiwan	0.4%	–	29%	29%	–	–	–
30	United Arab Emirates	0.4%	–	23%	31%	–	–	15%
36	Mexico	0.3%	–	30%	31%	–	–	20%
66	Kazakstan	0.1%	69%	23%	39%	19%	61%	3%
	Average for localized		68%	29%	31%	38%	31%	
	Average for localized (no Russian)					42%	27%	
	Average for all		30%	29%	31%			16%

Conversion rate is better for visitors who have visited at least once localized content. This behavior is consistent between countries. Effect is visible, though slightly smaller, even when bounce visits are filtered away. Therefore we conclude that people convert considerably more in local language: visitors convert 30 percent more [1] in their own language, on average. The effect cannot be explained by countries, because the difference is consistent in countries that have very varying conversion rates: China has only 16 % CR in average, and 18 % for localized content. France has high CR, 38 %, but it is even higher in local content: 50 %. However, in Russia and in Kazakhstan visitors convert more in English than in Russian.

Bounce rate is smaller on most countries in localized content. The Russian translation is different, for Kazakhstan and Russian bounce rates are higher in local language than the average bounce rate. As Russian had also problems in conversions, we think that there is something wrong with Russian translation. If we rule out Russian translation, bounce rate for localized content decreases from 31% to 27%, a 13% decrease.

16 percent of visitors have visited the subsidiary page during observation period. We cannot conclude if the site matches the performance targets for subsidiaries, because no such target is set. Some countries, like Czech Republic and Austria, redirect traffic from their local domain (www.Companyname.cz) to their subsidiary page. This practice leads most of the visitors for these countries to their subsidiary page – percentages vary from Austria's 58% to Czech's 77%. Countries that don't redirect the traffic from local domain to local subsidiary, like Finland and Germany, suffer from poor visit rates to subsidiary (1% and 5%, respectively).

Outside of the table it is interesting to see that almost all countries have at least some amount of visits in Finnish emphasizing the fact that Company is Finnish. Also, Slovakian visitors visit five times more the Czech subsidiary page than their own subsidiary page.

Table 5.6 lists most important observations from table 5.5 and applies statistical significance tests for those. G test introduced in 3.5.1 is used to calculate statistical significance. Because of large volumes, we decided to evaluate tests at 99% confidence level. Table shows comparable observations, their visits, related values, G score and tells if the difference is statistically significant. Table evaluates conversion rates and bounce rates in localized content and compares it to global content. Comparisons will be done both with Russian translation included and Russian translation filtered away. It also compares bounce rate and conversion rate in Russian to average bounce rate and conversion rate in other localized languages.

[1] Conversion rate rose from 29% to 38%.

Results show that Russian translation indeed performs worse than other languages. In fact, G test gave 100% statistical significance for it. If we filter out Russian translation, bounce rates and conversion rates are statistically significantly better in localized content. If we don't, conversion rates are still better but bounce rates are not better or worse.

Table 5.6: Statistical significance of localization insights

Observation 1	Visits	Value	Observation 2	Visits	Value	G score	Significant at 99%
CR in localized content	16533	38.17%	CR in all content	33377	28.55%	465.0	YES
CR in localized content (no Russian)	15803	41.75%	CR in non-Russian content	32336	29.41%	715.7	YES
BR in localized content	16533	30.78%	BR for all content	33377	30.64%	0.1	NO
BR in localized content (no Russian)	15803	27.33%	BR in non-Russian content	32336	29.85%	32.9	YES
Russian CR	730	20.21%	CR in localized content (no Russian)	15803	41.76%	146.4	YES
Russian BR	730	48.00%	BR in localized content (no Russian)	15803	27.33%	350.4	YES

5.1.4 Mobile

Figure 5.9 shows that the usage of mobile devices to surf the web is rising very rapidly, almost doubling every year on Company web site. However, it is important to note that even though the mobile web usage is very rapidly increasing, on Company web site it produced only seven percent of total traffic in 2013. Still, the trend is clear.

Figure 5.10 shows the differences of mobile usage in some countries. Figure shows that there are large differences between countries. As an example, Finland has three times the tablet and mobile usage compared to China. On average, European countries and USA have high usage on mobile devices and tablets, whereas countries like China, India and Russia have lower usage ratio. The interesting exception is Germany, it has a mobile usage rates like China, India and Russia.

Table 5.7 shows some key metrics for desktop, mobile and tablet devices from March 2013. Key metrics are the percentage of all visits, bounce rate, average visit duration, micro conversion rate, macro conversion rate, per-

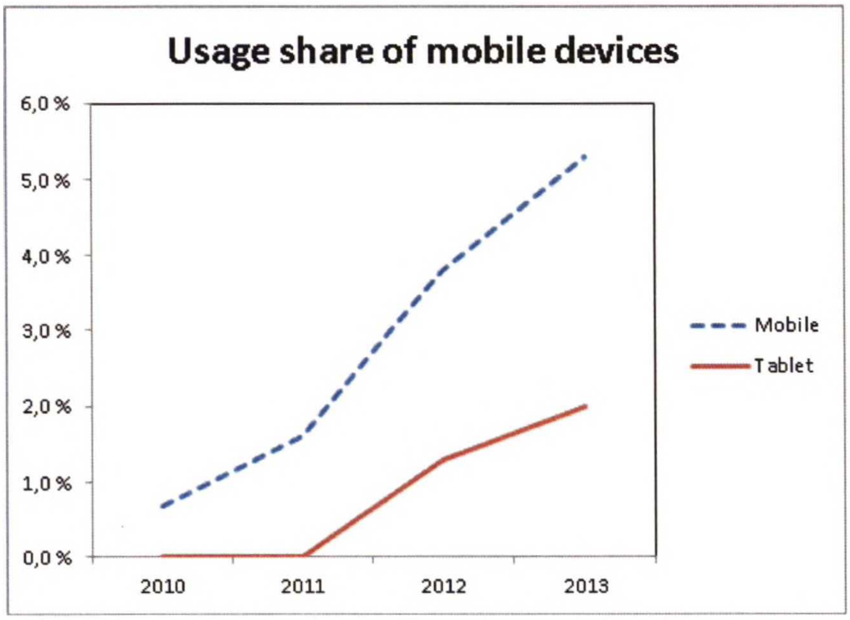

Figure 5.9: A timeseries of usage share of mobile devices on Corporate website.

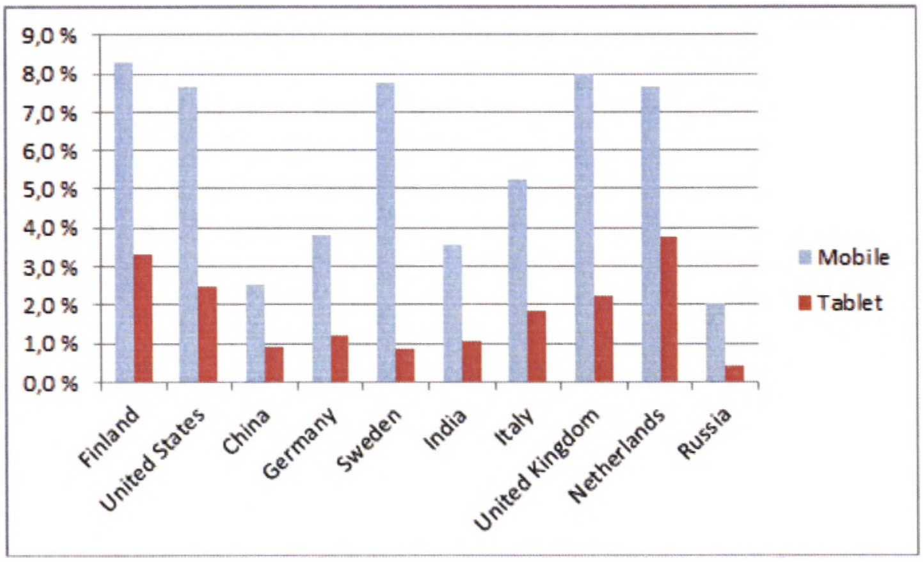

Figure 5.10: Usage share of mobile devices on selected countries. Values from table 5.4.

centage of total site revenue and value per visit. For web site valuation only the revenue generating goals were calculated for the table. Standard metrics indicates that mobile is the worst performer: it has the smallest average visit duration, smallest conversion rate and largest bounce rate. However, once we take our web site valuation model into account we see that mobile visits bring more value than tablet visits. Still, desktop visitors bring even more value per visit and they also account for most of the visits.

The observations show that conventional metrics, like average visit duration, conversion rate and bounce rate, do not always tell the whole picture. Macro conversion rate seems to be the best indicator for value per visit.

Table 5.7: Comparison of key metrics in desktop, mobile and tablet devices in March 2013.

Device	**% of visits**	**Bounce Rate**	**Avg. visit duration**	**Micro Conversion Rate**	**Macro Conversion Rate**	**% of value**	**Value / visit**
Desktop	92 %	31 %	4:47	26 %	0.5 %	95 %	0.70 €
Mobile	6 %	41 %	3:46	14 %	0.3 %	4 %	0.40 €
Tablet	2 %	33 %	5:04	22 %	0.2 %	1 %	0.30 €
All	100 %	32 %	4:43	24 %	0.5%	100 %	0.70 €

5.1.5 Section performance highlights

Table 5.8 shows the performance of key web sections. Table shows percentage of visits, average visit duration, conversion rate, bounce rate, percentage of value and value per visit metrics for six web site sections: products, downloads, subsidiaries, industries, services and investors. Bounce rate could only be calculated for visits where visits' landing page is inside site section. For most visits the landing page is front page making the bounce rates for site section results lower than bounce rate on average. Percentage of visits metric shows the amount of visits that visited site section compared to all site visits. It is important to note that one visit can belong to multiple segments. The table does not list visits to front page.

Product section has most visits and it is also most valuable, as one would predict. Services section has the highest value per visit, because trainings are under services section. However, only 5 percent of site visitors go to services section. Most sections have low bounce rate, less than 10 percent. There is two exceptions: subsidiaries and investors. They both have a bounce rate of over 25 %.

Average visit duration has a large variation: from subsidiaries section's 05:07 to services section's 11:20. Investors section's duration is also low, 05:20. Other sections have an average visit duration of eight to nine minutes.

Table 5.8: Performance of key web site sections.

Section	**% of visits**	**Avg. visit duration**	**Conversion Rate**	**Bounce Rate**	**% of value**	**Value / visit**
Products	28 %	07:58	43 %	9.5 %	35 %	0.90 €
Downloads	22 %	09:53	76 %	5.6 %	18 %	0.60 €
Subsidiaries	13 %	05:07	21 %	25.4 %	11 %	0.65 €
Industries	7 %	08:52	29 %	9.0 %	12 %	1.20 €
Services	5 %	11:20	43 %	6.9 %	32 %	4.70 €
Investors	4 %	05:20	10 %	35.4 %	5 %	0.80 €

5.2 Traffic sources

Table 5.9 presents the data that shows how visitors end up to Company website. Table presents five segments: brand search traffic, search engine traffic that has a Company name in keywords, non-brand search traffic, search engine traffic that does not have a Company name in keywords, paid search traffic, direct traffic, referral traffic and social media traffic. For these segments, percentage of visitors, average visit duration, conversion rate, bounce rate, percentage of value and value per visit metrics are displayed. For value calculations, only revenue generating goals were considered.

Table 5.9: Analysis of traffic sources.

Source	**% of visits**	**Avg. visit duration**	**Conversion Rate**	**Bounce Rate**	**% of value**	**Value / visit**
Brand search traffic (approx.)	47%	5:29	31%	22%	64%	1.00 €
Non-brand search traffic (approx.)	8%	2:21	8%	63%	3%	0.30 €
Paid search traffic	0.4%	1:52	12%	41%	0.1%	0.10 €
Direct traffic	30%	4:23	24%	33%	23%	0.60 €
Referral traffic	14%	3:51	17%	35%	9%	0.50 €
Social Media traffic	0.5%	4:45	14%	23%	0.3%	0.50 €
All	100%	4:43	25 %	30 %	100%	0.70 €

For Company web site Google accounts for 89 % of all search engine visitors. Baidu has a share of 4 percent and Bing has a share of 3 percent. Other search engines have very small shares. As discussed in section 2.5, Google decided to hide the keywords from search engine users that are logged in while making search queries. For Company web site it means that 30 percent of keyword data is lost. The search engine traffic presented in table 5.9 is divided to brand search traffic and to non-brand search traffic. As one third of keyword data is missing, it is impossible to make the division perfectly. For available data we calculated to ratio of brand queries to non-brand queries, presumed that the ratio is same for search queries with hidden keywords and applied linear interpolation to get the numbers presented in the table.

Brand search traffic is the largest and most profitable segment and it has both lowest bounce rate and highest conversion rate. It has a value of visit of 1 €, which is considerably higher than any other segment. Brand search traffic accounts for 64 percent of web site value. Direct traffic, referral traffic and social media traffic all have a very similar value per visit, 0.50 € - 0.60 €. Interestingly, social media traffic has low bounce rate, but it also has low conversion rate. Direct traffic and referral traffic have higher bounce and conversion rates. Social media traffic's volume is minor, it accounts only for half a percentage of all web site visitors. Non-brand search traffic and paid search traffic are clearly the word performers. They have highest bounce rates, lowest conversion rates, shortest average visit durations and therefore lowest value per visit: 0.30 € and 0.10 €, respectively. Non-brand search traffic is 8 percent of all traffic whereas paid search traffic is only 0.4 percent. During the time of measurements there was one search engine paid marketing campaign running, and it clearly was not a success.

Figure 5.11 presents the percentage of value and percentage of visits metrics on a graph. It demonstrates the dominance of brand search traffic, the minority of social media traffic and the poorness of both non-brand search traffic and paid search traffic. However, it is important to note that social media traffic and paid search traffic are the two most easily increasable traffic sources.

5.3 A/B tests

Exploratory behavior analysis on Company web site revealed the performance of different sections on the Company website. For example, careers section, contact map and localization seem to be performing well. Those features are used, and a considerable amount of visitors to those sections convert. Contact

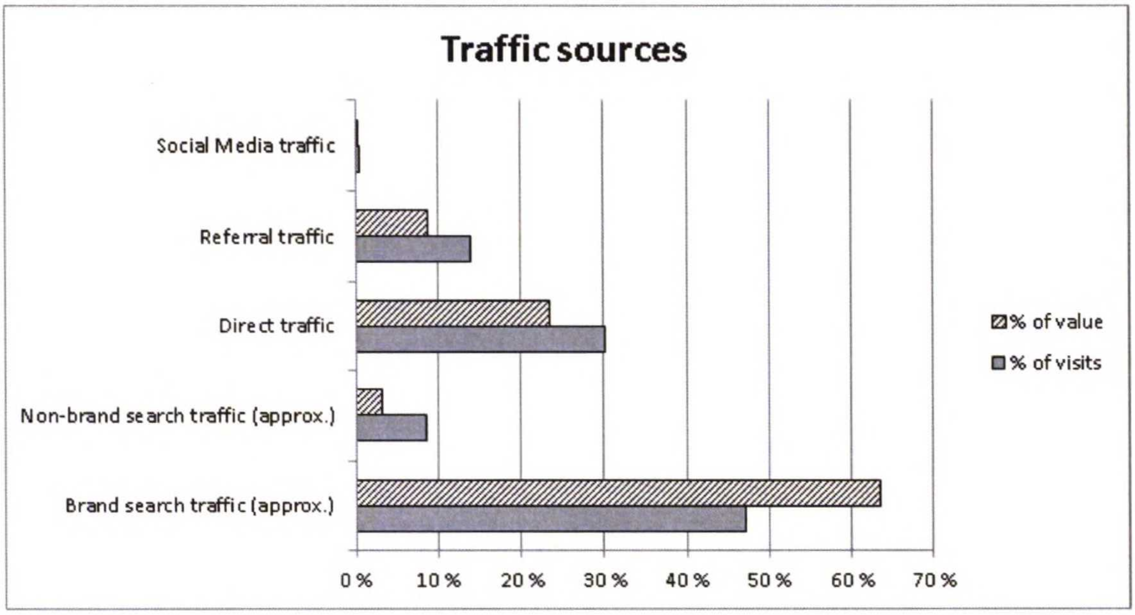

Figure 5.11: Traffic source analysis comparing visits and the amount of value they create.

map conversion rate, the amount of visitors interacting with map compared is very high, more than 80 percent. Some sections of the site perform poorly, and those sections have been subjected to A/B testing. Click-through rate on main site internal advertisement area, front page sliders, is very poor. We conducted multiple experiments while trying to better the performance. Also, the conversion rates for contact forms were very poor and trainings did not perform up to expectations. An A/B tests were designed for both contact forms and for trainings section of the page.

The statistical significance of the A/B test results was measured with G test, as discussed in section 3.5.1. The A/B test result tables have "statistical significance" column that tells the probability in percentages that the observed difference is statistically significant. On each test one variation is selected as the baseline. Baseline has no statistical significance value. Other variations are compared to baseline variation. If a variation has negative statistical significance value, it means the probability that the variation works worse than the baseline. If a variation has positive statistical significance value, it indicates the probability that the variation works better than the baseline.

5.3.1 Contact forms

Traffic observations show poor conversion rates from contact forms, less than 10 percent. Previous research has shown that optimizing form by minimizing the amount of form fields tends to improve conversions [57]. We designed three variations: original with 13 fields for control, variation 1 with 9 fields and variation 2 with 5 fields.

5.3.1.1 Contact us form

We decided to test contact us form in two most used languages on the web-site, in Finnish and in English. The hypothesis was that the less the form fields, more conversions. The results in table 5.10 show conflicting results in different languages. In English, best version is the original and in Finnish the best version is version with least number of fields. However, even with thousands of experiment visits no statistically significant winner could be found. Therefore we rejected the hypothesis and, because no clear evidence could be found in a way or another, selected the original form to web site.

Table 5.10: Contact us form A/B tests

Variation	Experiment Visits	Conversions	Conversion Rate	Compare to Original	Statistical significance
0: 13 fields, English	563	40	7.1 %	–	66.8 %
1: 9 fields, English	612	35	5.7 %	-20 %	–
2: 5 fields, English	144	4	2.8 %	-61 %	-93.96 %
0: 13 fields, Finnish	34	0	0 %	–	0 %
1: 9 fields, Finnish	113	6	5.3 %	–	–
2: 5 fields, Finnish	98	8	8.2 %	–	59 %

Different languages show conflicting results.

5.3.1.2 Request a Quote form

Originally, the same Contact Us form was used as a Request a Quote form as well. For this test, we designed a new Request a Quote form with 5 form fields and different title. Hypothesis was that the tailored form performs better than the original form. We ran this test in English, in German and in Finnish versions of the site. The combined results can be seen in table 5.11. It turns out that the hypothesis was correct: tailored form performs better and the difference is statistically significant with 95 % confidence. This test shows a 160 % performance improvement but that figure might not be accurate, because the traffic volume for request a quote was low. The difference is statistically significant, 160 % improvement is not.

Table 5.11: Request a Quote form A/B tests

Variation	Experiment Visits	Conversions	Conversion Rate	Compare to Original	Statistical significance
0: 12 fields	199	14	6.9 %	–	–
1: 5 fields	33	6	18.2 %	+160 %	94.4 %

5.3.2 Trainings

Trainings section of the page has poor conversion rate, only about two percent of training registration form page visitors end up registering in training. We decided to try out different design to improve conversions. On training list there is originally a list of trainings. Each row contains training name, location, date, language and a "register" button. Hypothesis was that "register" button is too strong and it scares visitors so we decided to replace it with "view" button instead. We also made a third variation that had both buttons. "Register" button leads to registration form and "View" button leads to training information page. The results of the test can be seen in table 5.12.

Table 5.12: A/B testing on trainings list

Variation	Training list visits	Training page visits	Registration form visits	Conversions	Conversion Rate	Statistical significance
0: Register button	235	140	32	7	3.0 %	27 %
1: View button	127	62	7	3	2.3 %	–
2: Both	105	32	5	0	0 %	0 %

No statistically significant winner found.

The results in table 5.12 show that the volume of trainings is too low to make any conclusions. Original variation is best and probability that the difference is not by chance is only 27 percent, way off from typically used 90 % and 95 %. Any variation could be best performer. Therefore the result of this test is inconclusive. This test shows how unpredictable visitor behavior can be. The variation with register button drives more visits to training page (60%) than the variation with view button (50%) even though register button leads to form and view button leads to training page. In all variations, however, clicking the name of the course leads to training page. The difference is statistically significant with 95 % confidence.

5.3.3 Slider lift-ups

Company web site has a slider element on the front page that is typically seen on news-focused web sites to advertise main news. Slider has five items and it shows a new item automatically every six seconds. The slider element is the most important content advertising area on the website. Once we set up the web analytics we immediately saw that the slider element is not working as well as expected, only 2 percent of front page visitors were clicking slider items. We even found out the slider element to be among the least clicked elements on the front page, which was not the intention at all. We decided to run an A/B test to find out the optimal number of items we should use and to find out the optimal time interval between item changes. Because some items on slider are more popular than the others and they are being clicked more, for the time of A/B testing we randomized the order of items. Without randomization the difference between three and five items could be explained by the different performance of slider items, not by the amount of items themselves. The results from that test can be seen in table 5.13.

Table 5.13: Front-page Slider A/B test

Variation	Views	Clicks	Click-through Rate	Statistical significance
0: 5 items, 6 seconds / item	5902	113	1.91 %	–
1: 5 items, 8 seconds / item	7861	154	1.96 %	14.8 %
2: 3 items, 6 seconds / item	2304	32	1.39 %	-93.6 %
3: 3 items, 8 seconds / item	2070	28	1.35 %	-94.2 %

The numbers do not show a clear winner. Five items seem to work better than three items. There is practically no difference between 6 and 8 seconds change intervals. More importantly, after the test it became evident that performance of the slider cannot be improved with simple changes. We planned a more radical approach but that design did not finish during this thesis.

Chapter 6

Analysis on web site behavior

We used exploratory behavior analysis to gather the data for chapter 5. This chapter presents further analysis on the data. First it analyzes the technology results, then it ponders about mobile usage and speed, discusses localization and subsidiary page results, analyzes the social media as a traffic source and finally compares the usage of the old Company web site to the new web site.

The numbers presented in chapter 5 show that the conventional, standard web metrics are not always good predictors for outcomes. For example, in mobile observations in table 5.7 average visit duration, bounce rate and conversion rate are not good predictors for value the segment provides.

For total web site value estimation it is important to consider both the revenue generating and cost saving parts of the web site, as discussed in section 3.1. Revenue generating parts of the web site was heavily used for the results in chapter 5. Cost savings are useful when estimating the total value of the web site – they are not useful when analyzing different parts of the website. Therefore cost saving goals were not used in chapter 5.

6.1 Technology

Literary research shows that faster page loading times increase conversions. Kaushik reports that 1 second delay in webpage response can result in a 7 % reduction in conversions [30]. Also, Clifton [11] reports two studies from 2006 and 2009. First study reports that web site visitors are expecting a site to load in less than 4 seconds. Later study from 2009 reports similar results, but the threshold is 2 seconds. The Company's website's average loading time is 7 seconds. However, our results suggest that Company web site visitors are not that sensitive to speed: results in figure 5.7 shows that visitors convert well when loading times are less than 7 seconds. Still, Company web site is relatively slow.

Resolution results presented in section 5.1.2.2 shows that web site is designed for large monitors and therefore for high resolutions. We noticed that for 1024x768, small desktop resolution, the site would look better if tablet's responsive design was applied. 60 percent of site visitors do not have optimal experience, because their screen height in pixels is not high enough. Numbers show that today web site does not work optimally from resolution perspective. In the future, though, where screen resolutions are likely to grow, issues are likely to diminish just by waiting for time to pass.

Browser results shows that the usage of non-supported browsers is in rapid decline - in 2013, only three percent of visitors used non-supported browsers. It is interesting to note that they are still used. Three percent of the traffic still means roughly 50 daily visits. The usage share of browsers is divided, it seems to be important to support all major browsers. Supporting only a handful of browsers would rule out most of web site visitors.

2 percent of web site visitors are using IE7 on 2013. That means roughly 1000 monthly visits. If we assume that IE7 users behave similarly to average web site visitor, revenue per visit would be 0.70 €. There we can easily calculate that supporting IE7 would increase revenue from web site with 700 € per month. It is also important to note that the usage share of IE7 is declining. We conclude that not supporting IE7 was correct choice, as supporting it would require significant changes to website's HTML and CSS.

Luckily, technology related issues like screen resolutions, computer CPU speeds, internet connection bandwidths and browser versions are all increasing and likely to continue increasing in the future. So problems related to these are becoming less and less severe as time goes by. Today the web site is not working optimally, but the web site is an investment for next 5-10 years.

Following list concludes most important insights from traffic observations of technology:

- The site would look better with 1024x768 resolution if tablet's responsive design was applied
- Web site's average load time is 7 seconds, slower than practitioners' recommendations of 2 to 4 seconds.
- Not supporting IE7 was correct choice: in 2013, only 2 % of web site visitors were using IE7.
- Supporting a wide variety of browsers is important.

6.2 Mobile

Results show that the use of mobile devices, tablets and smartphones, is on a rapid increase. Three years ago less than one percent was using mobile devices to browse Company website, and in 2013 the share is already eight percent. The mobile usage share cannot continue to grow as fast in the future, but we see no reason to presume that it would not increase in the future. From the usage share point of view this was correct timing to support mobile devices.

Web site valuation results indicate that mobile visitors are less valuable to Company than desktop visitors. According to results in table 5.7 desktop visit's value is 0.70 €, mobile visit's value is 0.40 € and tablet visit's value is 0.30 €. As mentioned in section 4.3 we could filter out most of the web usage by Company employees in desktop, but we could not filter out the Company employees' mobile usage. That might make mobile visitors' web usage less accurate than desktop usage. We still think we can assume that mobile visits are less valuable to Company than desktop visits. It is easier to complete major goals, like contact request or training registration, in desktop with full keyboard than in mobile.

Previous studies show that people convert more when the site is fast [11, 30], and our results in 5.1.2.3 support those studies. Mobile loading times on Company web site are high, 10-15 seconds – more than practitioner's recommendations. Conversion rate might be better, if the responsive site was faster. Responsive design requires that mobile sites contain the same markup as desktop, but the elements on the page are reformatted or hidden. The approach differs from mobile-optimized sites, where site is fully optimized for mobile. Therefore responsive design is slow on mobile without special optimizations. No such special optimizations have been made to mobile website.

We did not estimate the effect of responsive design to mobile behavior, because all mobile visitors experience the responsive design. Numbers cannot show what effect responsive design has to conversions. We think that it is safe to assume that the value per visit would be lower without responsive design.

It is possible that even though visitors do not convert as much in mobile and their conversions are less valuable than conversions in desktop, surfing mobile sites increase conversions in desktop. Quantitative data analysis cannot answer that, a qualitative data, for example a survey, would be needed.

Following list concludes most important insights from traffic observations for mobile:

- Mobile web usage is increasing rapidly, showing an annual growth rate of almost 100 %.
- Responsive mobile site is slow, average loading time is over 10 seconds.
- In 2013, 8 % of web site visitors are mobile or tablet visitors and therefore experience the responsive design.
- Numbers show that mobile and tablet visitors are not as valuable as desktop visitors - but that might not be the whole picture.

6.3 Localization and subsidiary pages

Localizations seem to work well, as results show that visitors convert considerably more and bounce slightly less in localized content compared to English content. However, Russian translation works worse than English version. This can be seen in Russia and in Kazakhstan, but in Ukraine Russian translation works slightly better than English version. There are two possible explanations: either there is something wrong in Russian translation or Russians prefer to gather information in English, not in their own language. Visitors from Russia, Kazakhstan and Ukraine account for three percent of web site visitors, so it is not a major issue. Actually, the amount is approximately same as the amount of visitors using non-supported browsers.

Subsidiary pages are not very popular in terms of visits, on average 13 percent of visitors visit subsidiary page. Table 5.8 shows that the average visit that contains visit to subsidiary page is worth 0.65 €. That is slightly below the site average of 0.70 €, and second worst for site sections mentioned in the table. Conversion rate is also poor, 21 percent. Approximately three percent of contact requests are sent from subsidiary pages.

Localizations make tracking more complex, as web analytics tools do not recognize that different URLs provide the same content, just in different language. Therefore valuing and analysing content requires customizations for the tool.

Following list concludes most important insights from traffic observations of localization and subsidiary pages:

- Company web site visitors convert 45 % more and bounce 13 % less in local language than on average when Russian translation is filtered away.
- Russian translation should be evaluated. Localized content works better in all other languages, but Russian translation is exception.

- Site should be translated to Swedish. Localized content works generally better, and Sweden is among the top ten visited countries, but it does not have its own translation. On comparison, France is 14th most visited country, but it has French translation.

- Kazakhstan attracts only 0.1% of web site traffic and has its own subsidiary page. Other subsidiary pages are visited considerably more.

- Slovakian visitors visit 5 times more Czech subsidiary page than their own subsidiary page.

- Poland, Switzerland and Turkey are among 25 most visited countries but do not have their own subsidiaries.

6.4 Site sections

Site sections results have more positive metric values than traffic source results or mobile results. That is because other results include visits to all pages, site sections results have only part of all visits. The global front page is the most popular landing page and therefore it has most of the bounces. Site sections have less landing pages and therefore they have less bounces. Because site section results omit most of the bounced visits, the metrics like average visit duration and conversion rate are better compared to all visits.

From the site section results it is interesting to note that industries have a higher value per visit than products even though conversion rate is lower. It indicates that industry content encourages visitors to contact Company more than product content. Subsidiaries and investors section have low average visit duration. Downloads have a high average visit duration, which might indicate that it takes too long to find out the file visitors are looking for. Services section has highest average visit duration, more than 11 minutes. That is definitely a positive sign that services content engages visitors for that long.

Most sections have low bounce rate, less than 10 percent. There is two exceptions: subsidiaries and investors. Subsidiaries act as a front page for some subsidiaries. That explains the high bounce rate. Global front page also has higher bounce rate than the bounce rate of pages deeper in web site structure. Investors have a high bounce rate as well. That might be, because investors visit the site just to see single press release or to check the stock value and then leave the site. High bounce rate in investors section is not necessarily a negative metric.

Following list concludes most important insights from section performance highlights:

- Products section has most visits, 28 % of all visits, and it also brings most of the value, 35 % of total value.
- Visitors spend over 11 minutes on a visit that contains visit to services page. That is high compared to average visit duration, about five minutes.
- Industries section's content encourages visitors to contact Company more than product section's content making industry section visit 30% more valuable than visit to product section.
- Subsidiaries and investors sections have high bounce rates compared to other site sections, more than 20 %.
- Services section has the highest value per visit (4.70 €) and industries section has the second highest value per visit (1.20 €). Average visit value is 0.70 €.

6.5 Social media

According to Rishika et al. the customers that participate in social media create 5.6 percent more revenue. These customers also visit stores 5 percent more than customers that don't engage in social media. [52] These results show that social media is an effective tool for businesses to engage their users and increase revenue. The article recommends that companies should encourage its customers participation to social media discussions.

Company uses popular social media services as a part of marketing. Services include LinkedIn, Twitter and Facebook. The web site has social media activity buttons, like Tweet for articles and LinkedIn recommend for products. However, according to our web usage analysis, those activity buttons are not being clicked.

Results on traffic sources presented in 5.2 show that visits from social media are interested in the content, as bounce rate is low and average visit duration relatively long. However, conversion rate is low and therefore average value for visit is also below average, 0.50 € compared to 0.70 €. Results also show that volume of social media traffic is minor, only 0.5 percentage of all traffic.

This thesis did not have social media discussion analysis so we cannot know how popular the Company is on social media.

6.6 Comparing old site to new site

Results in section 5.1.1 show that the new web site vastly outperforms the old website. Average visit duration has increased 32 percent and bounce rate has decreased 11 percent. These metric values are positive and they indicate that the new web site is more engaging to visitors than the old website.

The new site attracts more visitors than the old site. During the site launch there was no marketing campaign launched, so it does not explain the increase in visits. During five months observation period the direct visits and search engine visits to site rose, and referral traffic dropped. The traffic growth can be attributed to increased direct visits and to visits from search engines. Increase in search engine visits can be attributed to better Search Engine Optimization (SEO), but it is difficult to know why direct visits rose.

Chapter 7

Discussion

This section discusses about the results of the study and generalizes results. First, chapter presents discussion about results generalization, then it lists and evaluates experiences on research methods and customizations, tells the most important contributions of this thesis, tries to predict the future web analytics and finally gives some pointers for further research.

7.1 Generalizing results

We have listed refined research questions on section 4.4. We also listed 10 hypotheses based on research questions. This section lists hypotheses, accepts or rejects them and evaluates their generalization potential.

Table 7.1 lists hypotheses, tells if results from this thesis support hypothesis and evaluates the finding's generalization potential. Results support hypothesis column on the table tells if the results support hypothesis and it is evaluated on a scale of one to three plus signs. A minus sign tells that the results did not support hypothesis at all. Generalizable column tells that if we presume the hypothesis to be true, how well the result can be generalized to other web sites. Generalization potential is also evaluated on a scale one to three plus signs. A minus sign tells if the hypothesis cannot be generalized at all.

	Hypothesis	Results support hypothesis	Generalizable
1	Visitors convert more in their local language	+++	+++
2	Visitors bounce less in their local language	+	+++
3	Visitors convert more when site is faster	+	+++
4	Providing responsive design to mobile visitors is important	++	++
5	Web analytics can be used to support decisions	+++	++
6	Usage data justifies technology choices for Company web site	++	-
7	B2B visitors visit the site mostly in weekdays	-	+
8	New Company web site outperforms old web site	+++	-
9	Small web page design changes can change visitor behavior	+	++
10	B2B web site's commercial value can be measured	++	+

Results clearly support hypothesis 1, visitors convert more in their local language, and we think that the hypothesis can be easily generalized. Hypothesis 2 states that visitors bounce less in their local language. The results support hypothesis 2 if we filter out Russian translation. However, if we count in the Russian translation, there is no statistically significant difference in bounce rates between localized content and global content. Therefore the results only indicate that localization reduces bounce rate, but we think that the generalization potential is good. We could not find any studies about localization's effect to conversions or to bounces.

Hypothesis 3, visitors convert more when the web site is faster, is strongly backed by previous studies [11, 30]. However, our results only indicate that speed affects conversions.

It is not trivial to decide if hypothesis 4, providing the responsive design to mobile visitors is important, is true. Literary review supports the hypothesis [11, 29], practitioners argue that because the usage of mobile devices to browse web is increasing, visitors expect tailored web site. On 2013, 8 % of web site visitors were mobile visitors, and annual growth rate was almost 100 % so Company web site usage supports the hypothesis. However, our results indicate that desktop visits are more valuable than mobile visits. Once we applied the web site valuation model and analyzed the average value of visits from different devices on the Company web site, we found the desktop visit's value to be 0.70 €, mobile visit's value 0.40 € and tablet visit's value only 0.30 €. However, web analytics cannot tell if browsing the mobile version of the site increases the likelihood of conversions on the desktop. Therefore we gave a rating two to "results support hypothesis" and rating two also to generalization potential of the hypothesis.

Literary review revealed that the key benefit of web analytics is to base decisions on facts instead of expert opinions. Therefore hypothesis 5 is backed by almost all previous studies [23, 35, 44, 46, 48, 64, 66], and also our results show that we were able to get insights that can be used to guide decisions. However, leveraging web analytics to support business decisions is not trivial. Instead, it requires manual labor from analyst to get the insights that can guide decisions. First, the important metrics have to be defined and then the results need to be analyzed carefully. Implementing web usage tracking to web site is not enough.

Hypothesis 6 presumes that web usage data justifies technology choices for Company web site. We observed browser usage shares and resolution differences on the web site. We found out that supporting a wide range of browsers is important, and that the usage share of non-supported browsers in Company web site is low, three percent in 2013. Visual page design is optimized for large monitors, but in reality the screen resolutions, especially screen height, was relatively small for web site visitors. However, presuming a 5-10 years lifecycle for the web site the resolution problems are likely to diminish in the future. The result is not generalizable at all and also no previous studies about Company web site exist.

Hypothesis 7 states that "B2B visitors visit the site mostly in weekdays". We found out that the web usage between weekdays and weekends varies heavily between countries. Asian and American visitors visit relatively more on weekends compared to weekdays than European visitors. However, as web site gets significant amount of visitors on weekends, we decided to reject hypothesis 7. We presume that the result is slightly generalizable.

Hypothesis 8, "new Company web site outperforms old website" was clearly supported by results. We studied six metrics: visits, visitors, pages per visit, average visit duration, bounce rate and contact requests. Only pages per visit metric showed negative change, all other metric value changes were positive. However, the standard web metrics showed no large changes, difference was 10-30 percent. More importantly, one of the main goals of the web site, contact requests, increased by 100 percent. That clearly shows that even though new web site does not get visited that much more, it is more effective. This result cannot be generalized – not every web site redesign is going to be as positive.

Hypothesis 9, small web page design changes can change visitor behavior, is backed by previous studies [32, 37]. However, out of four A/B tests we run for this thesis, only one was successful and most of the time we were not able to make any statistically significant difference between variations. Our results indicate that small web page design might alter visitor behavior, but that is not always the case. The result is not easily generalized as the visitor behavior on different web sites might not be similar.

Hypothesis 10 assumes that B2B web site's commercial value can be measured. We developed a web site valuation framework for this thesis and we were able to apply that model successfully for the Company web site. However, it cannot be trivially applied to other sites. Site has to have similar goals and also it might not be trivial to fill in the values that web site valuation model formulas mentioned in section 3.1 require. If company or web site has different business model the model presented in this thesis might not be a good fit and the model might need small or large customizations. For these reasons, a generalizable potential rating of one out of three was given hypothesis 10. Previous studies show that valuing e-commerce B2B site is viable [62, 64].

7.2 Experiences

This section lists the experiences we had during the thesis. The goal of this section is to evaluate different parts of the thesis and discuss about benefits and limits of the study. First, we discuss about used research methods: web site valuation, exploratory behavior analysis and A/B testing. After research methods we evaluate the tools, list the experiences about the customizations made for Company website and finally assess the quality of references.

7.2.1 Web site valuation

Cost-saving aspect of web site valuation defined in 3.1.2 was not used in the analysis in chapters 5 and 6. However, it is important for Company as they want to evaluate both the revenue generating and cost saving aspects of the web site. That information is useful when valuing the total value of a website.

In B2B context the purchasing processes of companies are generally long [29], from weeks to months. Also, the buyer is a company, not a person: the people who visit the site to browse and compare products from different vendors might not be the same person who makes the purchase. Therefore it is both difficult and meaningless to value visitor's value. Better approach is to evaluate visit's value. All visits that exhibit wanted behavior, like downloading a brochure, are likely to increase the probability of purchase. It does not matter if the visitor is the person who actually makes the decision or person who influences decision maker. Best solution would be to value visits from company, but recognizing visitor's company is unreliable and future privacy regulations might forbid it, as discussed in section 2.6.

Valuation of non-e-commerce B2B site is estimation at best, because the web site itself does not generate revenue and because web usage tracking has accuracy issues mentioned in 2.3.2. That is one issue out of four issues on the web site valuation model that we have identified.

Second issue is that because model values visits, not visitors, it might overestimate leads generation: either same visitor completes multiple goals at one visit or visitor completes multiple goals over multiple visits. We do not think this as a problem, because if single visitor completes many goals, like downloads a brochure, checks contact location and views reference story, the visitor is more likely to make an order and it is good that three goal completions from the same visitor are calculated.

Third issue is that web site valuation is both fair and unfair. It emphasizes the importance of most important goals at the expense of other behavior. On company website, registering to training and making a contact request requires lots of writing and therefore desktop visitors are more likely to complete goal than mobile users, who do not have external keyboards. On the other hand, valuation is fair because it estimates only the amount of revenue generated from website. It cannot measure if visitors that have visited mobile web site are more likely to convert in desktop.

Fourth issue is that the model does not try to evaluate the value in brand management even though web presence plays a key role in brand management.

Taking these issues into account, we still believe that the web site valuation framework presented in 3.1 provides value estimations that are justified and that this framework can be of use to other companies as well.

For some special cases, like estimating the ROI of online marketing campaign, it makes more sense to estimate the value of a visitor instead. When estimating ROI of online marketing campaign, valuing only the first visit would underestimate the value the campaign generated. We should also attempt to value consecutive visits from the visitor that first visited web site from the campaign, even though identifying a visitor is not perfectly accurate.

The most important metric that web site valuation model provides, is a value per visit. On this paragraph we compare it to properties of good metric in section 2.4.2.2. First property is *accessible*: as long as a reader understands what a visit is, the metric is self-evident, everyone understands monetary values. It is also *relevant* and *actionable*, as it is meaningful to use it to support decisions. It is *auditable*, as the valuation is based on certain formulas that have parameters that can be changed and the number of goal completions is based on real web site usage. Of course, the valuation is only as good as the numbers inputted to the formula. When set up correctly to analysis tool, like Google Analytics, the analytics tool provides the valuation for daily basis with small delay, less than a day. That makes value per visit a *timely* metric.

7.2.2 Exploratory behavior analysis

With the help of customizations and web site valuation model we were able to acquire many insights from visitor behavior. Chapter 6 lists the most important insights from different point of views. Insights are typically only applicable to the site being analyzed.

The exploratory data analysis was useful in the Company web site's case. We cannot predict that it will be advantageous to every website. Our insights were a result of patiently observing visitor behavior.

7.2.3 A/B testing

We ran four A/B tests during this thesis and one of those A/B tests showed statistically significant improvement in conversion rate. Three other tests were inconclusive. This is in line with previous studies, which show that most of the time web site designers are wrong at predicting visitor behavior [28, 39, 42].

Visitor behavior seems to be very hard to predict, as visitors behave in surprising ways. For example, in A/B test designed for trainings section of the Company web site we experimented with a list containing trainings. Originally each row on the list contained training name, location, language and register button. Training name is a link leading to a training page and register button is a link leading to registration form. We replaced register button with view button that leads to training page [1] instead of training form to see if that changes behavior. The result was surprising: visitors visited training page more with register button and less with view button even though with register button there was only one link leading to training page and with view button there was two links leading to training page.

Company web site has a traffic volume of more than one thousand daily visitors. We thought that the traffic volume was enough for A/B tests to provide enough visits to acquire statistically significant results. It turned out to be false assumption. Three tests out of four were inconclusive, meaning that there was no statistically significant winner found. Even though the web site gets visited a lot, not all sections of the web site get a lot of visits. This has three implications: 1) pages subjected to A/B testing should have large enough traffic volumes, 2) available time for testing should be long, spanning

[1] The training page has a link to registration form.

multiple months, and 3) variations in A/B testing should have bold design changes to see any difference in visitor behavior. Previous research shows that even small design changes can alter visitor behavior dramatically [37] - our results indicate otherwise.

When running A/B tests it is important to decide confidence intervals and time to run the test before the start of the test. During our tests the point where we have stopped the experiment would have affected the result. At one point the contact us form test was showing that variation one is winning with 90 % confidence. When we ran the test a month more, the winning variation was the original with 60 % confidence. We advise practitioners to be careful when drawing conclusions based on A/B test results with less than 95 % confidence.

7.2.4 Tools

Google Analytics is a powerful web analytics tool, but it has its limitations. By default, it collects versatile data and it supports analyzing the data from many different viewpoints. Filtering is powerful, as regular expression support is provided. The collected data can be customized. It also supports exporting data to do further analysis on external software. It is well documented and lots of literature and blogs are available to provide support, like [27] and [11].

GA's statistical analysis features are poor. It does not provide medians, standard deviations or distributions. It is not possible to get all the raw data to calculate those on external software, because GA only allows exporting aggregate data. Tracking is based on pages and URLs so it does not work well with AJAX sites or multilingual sites where different languages have different URLs for same content. Customizations are not as versatile as we would have hoped for. For example, custom events support three-dimensional hierarchy. For some parts of the site we would have needed four-dimensional hierarchy. Also, GA only allows five simultaneous custom variables for free version.

The terms of service forbid using GA to store any kind of personally identifiable information. [11] That rules out using GA for certain uses. For example, one use case of web analytics is to use the visitor IP information to recognize the company of visitor. That information can be used in sales lead generation even though the visitor did not directly contact company. However, that kind of use of web analytics is not possible with GA.

GA is using page-tagging methodology to collect usage data and therefore suffers page-tagging's downsides as discussed in section 2.3.1. We had two kinds of problems because it is not possible to analyze the data that is already on the system. First, comparing current site to old site was complex, because tracking was done differently, even though metrics and tool were the same. Second, for this thesis some customizations were either erroneous or suboptimal and they had to be changed. During the time of erroneous customizations the data is and stays "dirty".

Google Content Experiments, the A/B testing tool, worked well for dividing traffic between variations but it had other limits. It does not tell the statistical methods it uses to calculate statistical significance, so we decided to calculate the statistical significance using G-test instead of relying to the tool's numbers. On one test the tool decided winner too soon, with only four conversions. On some tests Content Experiments reported different numbers than what we collected by customizations. For those tests, values collected by customized methods were used. We were left under the impression that Google Content Experiments is meant for simple tests, like landing page optimizations and choosing between different layouts and pictures. For more demanding A/B testing the tool is not a good fit.

7.2.5 Customizations

The task of setting accurate and meaningful page tagging was more complicated than expected. Kaushik [29] mentions that it might take as long as eight months to implement properly. During this thesis the plan was to set up the custom analytics in January and only collect data afterwards, but in reality the custom events tracking was fine-tuned as late as March and goal definitions with goal valuation were modified in April.

One reason for this is that Company web site was not designed with goals in mind. If different visitor groups, desired user journeys and targets of the site are not considered in requirements phase of a web site project, it might be hard to define them afterwards. They should be defined before web site design, not after.

7.2.6 Assessing the quality of references

This thesis contains many different types of sources: journals, professional literature, web sites, blogs and conference papers. As web analytics combines data from computing science to marketing, academic sources are either from the field of computing science or from marketing.

During the literary review we were disappointed on the average quality of academic papers about web analytics. Few of them provided to be very useful, especially computing science papers. It seems that computing science sources do not have much to contribute to web analytics. Marketing sources were poor on average, as well, but many articles in Journal of Consumer

Marketing provided interesting and important insight into web analytics. Papers about A/B testing were, on the other hand, very useful and insightful. Also, the books from leading experts in the industry were of very high quality. Those books provided theoretical background bundled with practical advice.

Literary review provided a lot of general information about web analytics and its applications. However, there was little data available for web site valuation, particularly for non-e-commerce websites. Therefore the largest original contributions of this work revolve around web site valuation.

Web analytics is a very commercial field and it is driven mostly by technological advancements and commercial interest. There is academic interest as well, but that does not seem to be the driving force for the field.

7.3 Contributions of this thesis

The thesis has both practical and academical contributions. The goal was to develop the use of web analytics within Company further.

On the beginning of the thesis Company had a simple web analytics implementation with Google Analytics in their web site. Using web analytics effectively requires tailoring to web site's needs. During this thesis we defined a more sophisticated usage tracking, implemented it and also changed both definitions and implementations during the thesis. We customized events, goals, goal values and custom variables. We began on January and modifications were still made in April. However, after this thesis Company has a customized web analytics solution with Google Analytics that is constantly monitoring the web usage and the value of the web site. The solution is on production use and monthly dashboards are generated from the usage data.

We also evaluated using web analytics to improve web site performance with A/B testing. One test out of four showed increased conversion rate, so we think that further usage of A/B testing, should the need arise, is a viable idea. The increased performance on request a quote form is a contribution in itself.

Section 7.1 told academic contributions of the work. Out of 10 hypotheses we had, we evaluate that 8 can be generalized. Two of the hypothesis, "visitors convert more in their local language" and "visitors bounce less in their local language" were new, we could not find previous studies to back that up. Hypothesis 10, B2B web site's commercial value can be measured, was mentioned in literary review but the model we developed (section 3.1) was original contribution. Also hypothesis 4, providing responsive design to mobile visitors is important, was mentioned in previous studies but our approach that evaluated the value of mobile visitors was new.

7.4 Future of web analytics

Looking back, the development of web analytics has been closely tied to the development of web analytics technology. As discussed in section 2.2, web analytics have developed from measuring hits to page views, from page views to visits, from visits to visitors and finally from visitors to outcomes.

We think that reading Kaushik's book Web Analytics 2.0 is like glimpsing at the future use of web analytics. He recommends web analysts to discard the old model, where web analytics is only about analysing web usage behavior. Instead, he recommends adapting a holistic view of web analytics that contains, not only web usage behavior analysis, but also competitor analysis, social media analysis, experimentation and testing, voice of customer and multiple outcomes analysis. The same trend can be seen on another practitioner's resources [11] and also leading tool, Google Analytics is expanding its features beyond traditional web usage tracking. Recently Google has invested to new features like Content Experiments for A/B testing, social media interactions analysis and cost analysis for marketing channel analysis [2].

Web analytics is becoming a vast umbrella term containing more than originally intended web usage tracking. This will widen the gap between industry and academia, as academia still prefers to use web analytics only in the scope of web usage tracking.

Tools nowadays are powerful and easy to use - and the tools are likely to get better. History shows that the web analytics have been more and more adopted [11] and we see no sign that the trend would turn. Market leader in web analytics tools is free, so there should not be a reason not to facilitate the benefits of web analytics for public websites.

7.5 Further research

Benefits and limits of web analytics seem to be well understood and tools support them well. Tools don't advertise their disadvantages, but academia and practitioner's resources are well aware of the disadvantages as well as advantages. Most assumptions made in Google Analytics are reasonable and they will suit to most use cases.

Valuation of a web site, on the other hand, has been underresearched. It is trivial to value e-commerce websites, but for other kinds of web sites the issue is harder. This thesis provides a web site valuation model presented in 3.1. It is meant to valuing B2B web sites that do not have e-commerce capabilities but which target to drive sales. Model does not suit to valuing other types of websites.

Web site valuation model could be developed further. It could be expanded to support valuing a visitor or, more interestingly, visitors from the same company. Another expansion possibility would be to include support to other types of web sites, like non-profit websites. Also, more research on how to effectively define and value outcomes is needed.

Another pointer for further research is the Russian translation on Company web site. We are not sure if the translation is faulty, or if Russian visitors react more positively to the English version of the site, not localized version.

Chapter 8

Conclusions

To recap, below is the list of research questions we set at the start of the thesis:

1. How to study web site behavior using web analytics?
2. How to improve web site performance using web analytics?
3. Can web analytics be used to measure B2B web site's commercial value?

With web analytics it is relatively easy to measure web site behavior. Web analytics is the only method to acquire web usage data. We found out that web site behavior should be studied in a diverse fashion. The goal of web site behavior study is to find *insights*, important and actionable findings that drive decisions. It is to be noted, though, that web analytics is good at telling *what*, but bad at telling *why*. The web analytics tool used during the thesis was Google Analytics.

For this thesis we studied visitor behavior from many angles. We observed visitor behavior from a technology viewpoint, observed the effect of site speed, localizations and mobile devices to web site usage and analyzed the relative performance of site sections and traffic sources. We managed to find some insights that are useful for the Company when deciding about the web site, and we also found some insights that we think can be generalized to other web sites. Visitor behavior is improved when they are browsing the web site in their local language. In other words, they *convert* more. Also, they convert more when the web site is faster. Contrary to our hypothesis, visitors visited the Company web site as well in weekends as in weekdays. From mobile observations we found out that providing a responsive design to visitors is important, because 8 % of web site visitors were using a mobile device to browse the Company web site in 2013. Traffic observations also revealed the fact that the new Company web site outperforms the old web site.

We decided to use testing methodology called A/B testing to improve web site performance. In A/B testing the web site visitors are divided to two groups: a control group and a test group. A modified design of testable web page is shown to a test group, and the original design is shown to a control group. The target of a test is to find out which design brings more desirable outcome, which is usually the amount of visitors that converted compared to all visitors. A/B testing is a scientifically valid and relatively cheap methodology to test out different designs. Visitors are part of the test just by using the web site even though they do not know it.

During this thesis we ran four A/B tests and struggled to get any statistically significant changes between design variations. We were able to improve the performance of the "request a quote" form in one of our tests. Other tests were either inconclusive or the original design proved to be the best one. We learned that predicting visitor behavior is very difficult. Practitioners should prepare themselves to be wrong most of the time when predicting visitor behavior.

We found out three rules of thumb for successful and statistically significant A/B testing: 1) run A/B tests only on pages that have large visitor volumes, like thousands of daily visitors; 2) make bold design changes to variations, otherwise it might be impossible to see any change in visitor behavior; and 3) run A/B test for a sufficiently long time, at least for weeks.

Estimating the monetary value of a business-to-business web site that does not have e-commerce features was one of the main focuses of this thesis. In collaboration with Company employees and with tips from literature we defined a web site valuation framework for this thesis. The model is divided to two subcategories: 1) estimating the revenue generated from web site usage, and 2) estimating the value of cost savings from web site usage. Type 1 behavior increases sales and type 2 behavior saves costs, for example by providing automated support functionalities online.

The model provides three new web metrics: the total amount of revenue generated from website, the total amount of cost savings produced by web site and a value per visit. A value per visit metric gives a monetary value for a visit. It is a metric that provides timely actionable insights, and is easy to understand.

We think that the model can be of use to other companies as well. It can be used to estimate web site value, to estimate the value of future investments and it can also be used for return of investment calculations. In the future research, the model could be expanded to support also estimating the value of other types of websites, like non-profit websites.

At the beginning of the thesis the Company had a simple web analytics implementation in their website. During this thesis we developed the use of web analytics further both from the process viewpoint and from the technological viewpoint. The technical implementation made during this thesis is in production use for the Company and they make monthly dashboards out of that usage data. Also, this thesis has given an overview of other web analytics benefits, like estimating the value of web site and improving web site performance using A/B testing, to the Company. After this thesis the Company is more mature in its web analytics usage than before.

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