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Der Einfluss einer verbesserten Usability auf Konversionsraten

Analyse der Jobbörse Profesia.sk

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Analysis of the job searching portal Profesia.sk

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Wien, 25. September 2017

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Abstract

Conversion rate optimization is one of the top priorities for numerous online businesses. Companies want to optimize the number of purchases, email sign ups, registrations or other website performances. Nevertheless, when trying to increase the conversion rate they often neglect the usability aspect of the website. In this thesis, we examine whether improvements in the usability of a website also lead to an increased conversion rate.

In order to analyze this issue, we decided to run a series of A/B tests on the job searching portal Profesia.sk. After locating a usability issue, we proposed and developed a solution. Furthermore, we split the traffic in two halves and displayed the improved version of the website only to one half of the users. After reaching a significant sample size, we stopped the experiment and compared the conversion rates of both versions. By using the A/B testing method, we were certain that the differences in conversion rates were caused by modifications that we made and not due to seasonal trends or coincidence. In the majority of our experiments, we considered a conversion to be sending an application to a job offer.

The results of the experiments proved that there is a correlation between usability and conversion rate. Although in some experiments there was only a negligible shift in the conversion rate, especially in experiments which handled a serious usability flaw, the improved versions performed significantly better. In this thesis, we showed that enhancing usability leads to a higher conversion rate.

Abstract

Die Optimierung der Konversionsrate ist eine der Hauptprioritäten für zahlreiche Online-Unternehmen. Die Unternehmen wollen die Anzahl der Einkäufe, E-Mail-Anmeldungen, Registrierungen und andere Leistungen auf der Website optimieren. Um die Konversionsrate zu erhöhen, vernachlässigen die Unternehmen oft den Aspekt der Nutzbarkeit von Webseiten. In dieser Arbeit untersuchen wir, ob Verbesserungen der Nutzbarkeit von Webseiten auch zu einer erhöhten Konversionsrate führen.

Für die Analyse dieses Problems haben wir uns entschlossen, eine Reihe von A/B-Tests auf dem Job-Suchportal Profesia.sk durchzuführen. Nach der Identifizierung des Nutzbarkeitsproblems haben wir eine Lösung entworfen und entwickelt. Dann werden wir den Betrieb in zwei Hälften geteilt und verbesserte Version der Website wurde nur einer Hälfte der Nutzer dargestellt. Nach dem Erreichen einer signifikanten Stichprobengröße haben wir das Experiment gestoppt und die Konversionsraten beider Versionen verglichen. Mit der A/B-Testmethode waren wir sicher, dass die Unterschiede in den Konversionsraten durch die von uns durchgeführten Modifikationen verursacht wurden und nicht durch saisonale Trends oder Zufälle. In der Mehrzahl unserer Experimente wurde eine gesendete Bewerbung um ein Jobangebot für Konversion gehalten.

Die Ergebnisse von Experimenten zeigten, dass es eine Korrelation zwischen Nutzbarkeit und Konversionsraten gibt. Obwohl es in einigen Experimenten nur vernachlässigbare Verschiebung der Konversionsrate gab, vor allem in den Experimenten, die einen ernsthaften Nutzbarkeitsfehler erfassen, führten die verbesserten Versionen zu deutlich besseren Ergebnissen. In dieser Arbeit haben wir gezeigt, dass die Verbesserung der Nutzbarkeit zu höheren Konversionsraten führt.

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CHAPTER 1

Introduction

In recent years, the internet has become an essential tool for finding a job. According to the data presented in [1], in 1998, only 5.7 percent of people searched for jobs online. By 2003, the number increased to 11.5 percent. Moreover, a survey [2] conducted in years 2008/2009 showed that 86.1 percent of unemployed people with internet access were looking for a job online. Interestingly, a study [3] from 2004 found that internet job searching was associated with longer durations of unemployment in the years 1999/2000. However, a study [2] conducted around a decade later found that using the internet to search for jobs has decreased the duration of unemployment by about 25 percent. The study states (as one of the factors for this) design improvements carried out on the main internet job search sites.

The job portal Profesia.sk also had to go through this evolution process. The portal was founded as a Slovak company in 1997 and is currently owned by the Finnish media group Alma Media. Over the years, it has become not only the leading job searching portal in Slovakia, but, moreover, it has basically established a monopoly. In addition, the portal is established in the Czech Republic as Profesia.cz and in Hungary as Workania.hu and it is among the most visited job portals in both of these countries.

The objectives of the portal are very much dependent on the job market situation in the given country. At the time of the financial crisis in 2007-2008, the objective was to encourage companies to use Profesia.sk for job advertisement. However, with the improving economy and decreasing unemployment, it has become more difficult for the companies to find employees. According to Eurostat statistics, the unemployment rate in Slovakia in August 2016 was 9.5 percent, which is a decrease by 16.77 percent when compared to August 2015 [4]. Because of the low unemployment rates and the fact that the applicants are often not meeting the labor market requirements, it has become increasingly difficult for companies to find potential employees. Therefore, in the current job market situation, the goal of the job portal is to encourage people to send reactions to job offers.

Since sending a reaction to a job offer is what is now most valuable for the website, in this thesis, we will consider it as a conversion. In most ecommerce websites, the term conversion rate is connected with the number of people who complete an online purchase. However, the conversion rate can be defined as the percentage of users who take the desired action [5]. In our case, the desired action is sending a reaction to a job offer. Therefore, the term increasing the conversion rate in this context means increasing the percentage of users who send a reaction. In this thesis, we will examine the relationship between the usability of a website and the conversion rate.

Usability is defined by ISO 9241 as the effectiveness, efficiency and satisfaction with which specified users achieve specified goals in particular environments [6]. The first challenge in comparing usability and conversion rate is the fact that while the conversion rate is a purely quantitative attribute, usability on the other hand is a qualitative attribute which is difficult to assess. Since usability is difficult to measure and its impact on the revenues is not always instantly visible, it is often neglected by executives. They often care only about the conversion rate, focusing only on simple, cheap and short-term solutions. However, fixating on the conversion rate only can have a severe impact on the usability of the website. In this thesis, we will examine the importance of usability in connection to the conversion rate. For this examination we will use Profesia.sk, where we will conduct the experiments.

We will use an iterative approach to conduct the experiments. Firstly, we will analyze the usability of the website. In the next step, possible solutions will be suggested and the chosen solution will be tested using A/B testing. Finally, the results of the experiment will be evaluated. This process will be repeated for several use cases. After conducting and evaluating all the experiments individually, overall results will be assessed.

The analysis of usability will be done by examining the data about user behavior through the Hotjar tool and Google Analytics. Hotjar provides possibilities to gather feedback through online surveys or to analyze user behavior through heatmaps and visitor recordings. Although the heatmaps are based on the cursor position only, there is a very strong correlation between the position of the cursor and the gaze of the user. A study conducted by Huang [7] compared the gaze and cursor positions of participants. It proved that the positions were quite similar. Furthermore, Google Analytics will be used for examining overall user behavior on the website. Log file based web analytics has been used for the evaluation and improvement of website content in several scientific papers. Jana and Chatterjee [8] used information about page views, hits, user sessions and the location of users to analyze the content of The Energy and Resources Institute's website. However, Google Analytics significantly changed the whole process of website analytics by introducing a great number of complex functionalities. It is currently the most popular web analytic tool. Although Google does not publish data about the number of users, according to the tool Similartech [9], almost 50 million websites use Google Analytics, which is more than 25 percent of all websites. The tool provides a great amount of information which can be used for usability analysis. Research by Hasan [10] showed that using Google Analytics metrics such as percentage of site exits, bounce rate, average number of page views per visit etc., can identify general potential usability problems on the site overall and on specific pages. Last but not least, user feedback from the customer support department will be also analyzed.

For potential usability issues, possible solutions will be proposed. The proposed solutions will not necessarily introduce a new feature or functionality. They will only be improvements to an already existing functionality. Each solution will be prioritized based on the PIE framework [11]. In the PIE framework, solutions are assigned points for potential, importance and ease of implementation. Potential indicates how much improvement can be made on the pages. The pages which are performing the worst have the best potential for improvement. Importance expresses the traffic on the given page. Usability issues on pages with low traffic have lower importance than, for example, a homepage. Lastly, ease of implementation is evaluated. Since profesia.sk is a relatively old system, some adjustments can be extremely demanding and time-consuming. Each of these factors is given one to ten points. The solution with the most points will be tested using the A/B testing method.

A/B testing is the act of running a simultaneous experiment between two or more pages to see which performs or converts the best [12]. The page traffic will be divided into two halves. One half will be shown the original version of the website and the other half will be shown the new, improved version of the website. The main advantage of A/B testing is the fact that both versions are used in exactly the same environment. Without A/B testing, it is difficult to establish if the results are affected by the changes made or by some other external factors. For example, there could be a new solution implemented in December. The number of page views would decrease and we would suggest that our solution is not suitable. However, because of seasonality, the number of page views is always lower in December, compared to the rest of the year. Using A/B testing, on the other hand, assures exactly the same conditions for both versions. An A/B test can be properly evaluated only when reaching certain traffic. In other words, a test with few samples has no informative value. Fortunately, profesia.sk has relatively high traffic and therefore these tests can usually be evaluated within a few days. Except for the effect on the conversion rate (the number of reactions to job offers), we will also analyze if other metrics, such as page views, have not been negatively affected.

Ultimately, the overall results will be assessed. It will be determined which solutions had the highest impact on the conversion rate. Moreover, we will examine whether the changes actually led to usability improvements. We will also compare other metrics such as page views, the number of sessions, registered users etc. Last but not least, we will conclude whether the usability of the other group of users, the companies, was negatively affected.

The thesis has the following structure. After an introductory chapter, already existing approaches are described in chapter 2. Various research sources will be presented, mostly on the topics of job search portals, usability analysis using analytic tools and improving conversion rate. Since there are very few resources dealing with comparing the usability and conversion rate, it will be essential to find appropriate resources on both topics and combine the findings. In chapter 3, Methodology, we will describe the techniques and concepts used. We will focus on finding the usability issues mainly through heatmaps and analytic tools. Moreover, we will further define the A/B testing process and the statistics connected to it. The tools that will be used for the testing will also be described. In the next chapter, Results, specific experiments will be described. Apart from the description of the solution and the provided screenshots, the results of the experiments will be shown. The experiments will be evaluated based on the data provided by profesia.sk. Furthermore, the overall effect of usability on the conversion rate will be presented. In the Critical reflection chapter, we will evaluate the success of our findings. We will compare our results with similar researches. We will also discuss possible improvements for the process. In the last chapter, we will summarize our results and illustrate possible future progress. The thesis ends with a list of references.

CHAPTER 2

State of the art

In this chapter we will first analyze the usability of job search portals. We will then examine the relationship between usability and conversion rate. Next, we will compare traditional usability evaluation techniques with state-of-the-art techniques such as web analytics and cursor tracking. Furthermore, previously conducted experiments and approaches for raising the conversion rate will be described.

2.1 Usability of job search portals

The internet has had a significant impact on job search behavior. What is more, the impact is still growing, since the percentage of the population using the internet is also rising. Statistics from 2015 showed that 79% of 16 to 74 year-old people living in the EU used the internet at least once within the three month period prior to the survey [13]. The ability to use information and communication technology (ICT) provides the working population with the opportunity to search for a job using job portals. Nevertheless, one of the most common ways of finding a job is a personal referral. Many people find a job through friends and family. Therefore, in the last few years, the use of professionally oriented social networking web sites (SNWs), such as LinkedIn has become widespread. Moreover, even nonprofessionally oriented social sites, such as Facebook, have often been used for advertising job opportunities. According to Jattuso [14], general job boards attract lower quality participants since they are not focused on a single industry. Therefore industry specific job boards are gaining popularity. Nevertheless, general job boards are well-established. An article by Nikolaou [15] compared the effectiveness of finding a job using LinkedIn, Facebook and traditional job boards. In the paper, a set of hypotheses was proposed and these hypotheses were examined using online questionnaires. It was confirmed that job seekers were using job boards most extensively, and they found them to be the most effective. Moreover, they found the professional SNW LinkedIn to be more effective compared to Facebook. This paper showed that even though social networks widen the job search options, job boards still remain the most effective way of finding a job online.

The evolution of ICT did not change the job market from the perspective of job seekers alone. Companies invest a lot of resources in online recruitment. A paper by Howardson [16] examined the effects of usability expectations on internet recruitment outcomes. He defined usability expectations as the subjective beliefs that recruitment technology will be useful and will require little effort. Firstly, the authors of the paper created an internet recruitment website for a fictional technology services organization. The website was created by examining other career websites and consisted of six different subpages with detailed information about the company and the open positions. One group of participants used this website to obtain information about the company. The other group of participants were asked to download and visit SecondLife, a popular interactive three dimensional internet technology. The participants were asked to visit the company's location within the virtual world. The space consisted of four walls with posters showing screenshots from the static website. The room also contained sofas, chairs and a coffee table for users to interact with others. The participants were able to interact with each other as well as with the recruiter avatar, controlled by a member of the research team. The hypothesis that the interactivity would have a positive impact on the company's attractiveness was confirmed. Moreover, there was a positive relationship between usability expectations and usability perception. This was confirmed by the fact that users with high usability expectations were more attracted to the company if they found the technology usable. The relationship between an organization's career website usability and the probability that the job seeker will choose to work there have been examined in a number of other scientific papers [17] [18]. In all of these papers, it was confirmed that these two factors are strongly connected. Even though profesia.sk is not a career website, it can be perceived as a representative of the recruiting company. Therefore, usability is a crucial factor in gaining the reactions for job postings. In all of the previously mentioned studies, it was proven that the usability of the website has a positive effect on whether job seekers apply for the job. That is why we assume that improving usability will help us increase the conversion rate.

A paper by Musaa [19] studied the Malaysian job portal of the Sarawak Government. For the usability evaluation they used an expert evaluation done by five HCI experts. They evaluated the usability of navigation based on the search engine, length of pages, hyperlinks and location indication. Furthermore they evaluated page layout through indicators such as the use of colors, use of images, consistency and attractiveness. The evaluation uncovered a number of usability issues. The evaluators experienced problems with using search, they criticized the amount of text on the pages, the fact that critical content was at the bottom of the page, page formatting, coloring etc. Next, solutions were proposed. However, they were too general. The usability improvements stated in the paper, such as using fewer colors and keeping the content short, should already have been known and are not truly useful. Moreover, the paper only proposed the solutions without actually implementing them. Therefore, the hypothesis could not be proven.

In this thesis, we will focus on proposing specific solutions, which will be tested and evaluated.

To sum up, there are a number of papers studying the online recruiting process. The effect of the usability of a company's website on a job seeker's willingness to work for the company is obvious. In this thesis, we will examine whether the same effect also applies for job portals. In other words, if the usability is increased, will more people apply for a job on profesia.sk?

2.2 Relationship between usability and conversion rate

Very little research has been done on the relationship between usability and conversion rate. Although these areas are interconnected in real-life applications, as areas of scientific research they have mostly been studied separately. Usability is mainly studied by groups focusing on human-computer interaction. Since usability is an applied inter-disciplinary field, it requires input from areas such as software system design and cognitive psychology [20]. Conversion rates, on the other hand, are closely connected to ecommerce, which is a relatively new, but rapidly expanding field. Ecommerce is usually studied by groups focusing on business strategies and management. Lack of communication between these groups of people can also be seen in many online projects. UX designers are trying to make websites usable and defend the interests of the user. Ecommerce managers, on the other hand, often care only about revenues and conversion rate, with a lack of regard for what the users want. The close relationship between usability and conversion rate, and consequently revenues, is often overlooked. In real-life applications, as in research, great results could be achieved if more attention was paid to the correlation between usability and conversion rate.

Although not much research has been done in the area of the relationship between usability and conversion rate, there are papers dealing with usability cost-benefit analysis, which is a similar issue. The question asked by managers is always the same: Will the resources invested into usability improvements return in the form of higher revenues? There are a number of frameworks for cost-benefit analysis. Most of the frameworks take into consideration multiple factors.

A paper by Mantel [21] compares the costs and benefits of usability engineering by calculating the costs of different usability engineering processes such as user testing, surveys, responding, coding, analyzing etc. The benefits are then calculated by aggregating saved costs for decreased training, lower number of errors, decreased late design changes, decreased customer support and increased sales. A few example calculations are also stated. However, no comprehensive case-study is presented. Moreover, usability evaluation techniques were also counted in the costs. Traditional methods of usability evaluation, such as user testing, are considerably more expensive than conducting an evaluation using only online analytic tools. Furthermore, the paper only described general cases and made a lot of assumptions which were not supported by any research work. In addition, it is very difficult to estimate the future impact of usability improvements in the long term.

A paper by Rajanen [22] conducted a case study, where a small-to-medium size software development company participated in the 'Usability' project for two years. The project consisted of usability testing, paper prototyping, usability requirement workshops and, most importantly, improvements to usability. An increase in sales was a very important motivating factor for the company to participate in the project. On the other hand, reduced training and support costs were mentioned only marginally. The general concern with investing in usability is the fact that the costs of usability are tangible and quantifiable whereas the benefits are often not visible in the short term. That is why in this study, the usability cost-benefit models did not succeed in persuading the management to continue the usability improvement processes.

Most of the papers dealing with usability cost-benefit analysis consider only traditional usability evaluation methods and count with the whole variety of benefits, from a better company image to reduced customer support costs. Nevertheless, as stated in the paper by Rajanen [22], management is mostly interested in revenues and sales only. That is why in this thesis, we will be analyzing the relationship between usability and the conversion rate only. Moreover, in this thesis, Google Analytics and Hotjar tools will be used for the usability evaluation. These tools are considerably cheaper than conducting expert interviews or user testing. The cost of usability engineering is therefore significantly lower.

2.3 Usability evaluation techniques

2.3.1 Traditional usability evaluation

Research on usability evaluation and analysis has already been carried out for several decades now. Although the technologies are evolving very fast, the basic usability principles stay the same. This is proved by the fact that one of the most cited publications on usability is 'Usability Engineering' by Jacob Nielsen, written in 1994 [23]. However, with advanced web analytic technologies, new ways of usability assessment have been introduced.

Nielsen divided usability evaluation methods into four categories: formal, automatic, empirical and heuristic evaluation [24]. Usability can be evaluated formally by using an analysis technique. Automatic evaluation is done by an automated computer procedure. Empirical evaluation requires test users. One of the most popular evaluation methods is heuristic evaluation. Heuristic evaluation is based on looking at an interface and coming up with an opinion on whether it is good or bad. Ideally, the evaluators should have a certain set of rules prescribed. The experiments done by Nielsen proved that a single person can only reveal a limited number of usability issues [24]. During the experiment, the evaluators could find only from 20 to 51 percent of usability problems. However, aggregating the findings of four to five evaluators produces quite satisfactory results.

The main advantages of the heuristic method are that it is relatively cheap, easy to plan and can be done early in the development process. On the other hand, there are a great number of disadvantages. Firstly, the evaluation is usually done by educated people involved in the development process. The user base often consists of a great variety of different user groups with different mindsets and skills. What seems obvious to the evaluators might cause problems to the users. Moreover, since the evaluators usually use the website every day, they can possibly overlook huge usability flaws simply because they already know the system so well.

Another common usability evaluation method is empirical evaluation. Empirical methods evaluate usability through user testing [23]. There have been a great number of studies done in the field of user testing. Articles such as Eight is Not Enough [25] claim that the number of participants is essential. Earlier studies by Nielsen [23] claimed that user testing with even 5 participants could reveal around 80 percent of usability issues. Either way, user testing can be quite expensive and time-consuming. That is why it cannot be done after every small adjustment. On Profesia.sk, several rounds of user testing have been done. However, they were often connected to introducing new features or changing the website appearance. It is not feasible to conduct user testing iteratively after every small adjustment.

2.3.2 Usability evaluation using web analytics

In recent years, more and more emphasis has been put on automation of the usability evaluation processes. In the paper by Ivory issued in 2001, the Capture Support method is described as one of the automated usability testing methods [26]. In the traditional user testing, the evaluator takes notes about the actions of the user. In the Capture Support method, the events are recorded automatically using some kind of event logging. This approach is also known as a log-based analysis. In 1999, Okada developed the computer tool GUITESTER [27]. The tool ran on Microsoft Windows and it was a log-based usability testing tool. The tool recorded user interactions in the log files, detected and visualized patterns by using the proposed methods. The tool was obviously more efficient than a manual check of the log files. However, it required a higher number of participants and it was still not able to detect some types of usability issues. Log-based usability was the very first step towards using web analytics data for usability evaluation.

Web Analytics is the science and the art of improving websites to increase their profitability by improving the customer's website experience [28]. It is primarily used by businesses to help them attract more visitors, increase the average order value, improve the performance of the website or optimize the marketing activities. According to Waisberg [28], the objective of web analytics is to understand and improve the experience of online customers, while increasing revenues for online businesses. From this statement it can clearly be seen that there is an obvious correlation between usability and revenues. The results of web analytics are usually presented in the form of a graph or a chart. In the past, the data about the customers were kept in the database or in internal log files. Nowadays, there are a great number of open-source or commercial tools which store the data and provide a great number of visualization features. As already mentioned, the most popular analytics tool nowadays is Google Analytics. The data and metrics available in Google Analytics will be further described in the chapter Methodology. There are several scientific papers focused on Google Analytics [29] [30] However, the vast majority of them only focus on metrics monitoring. In this thesis, we will use Google Analytics, not only for measuring the website performance, but also for analyzing the usability.

A paper by Hasan [10] deals with using Google Analytics for usability evaluation. The research presented three ecommerce case-studies. It compared the findings indicated by Google Analytics with the findings from heuristic evaluation done by a group of experts. They analyzed the websites in six different areas: navigation, internal search, architecture, content and design, customer service and purchasing process. Alternatively, 13 Google Analytics metrics were considered for the evaluation. They were chosen either individually or in combination. Metrics such as average page views per visit, bounce rates or order conversion rates were considered. For the navigation analysis, the results derived from web metrics were fairly similar to the heuristic evaluation results. Metrics used for navigation evaluation were: bounce rate, percentage of visits using search, average searches per visits etc. For evaluating internal search, similar metrics were used. Moreover, the ratio of search results to site exits was considered. In two cases, the ratio was higher, which indicated that the presented results were not relevant. This usability issue was confirmed by the heuristic evaluation. For architecture analysis, among others also the percentage of visits with low click depth was analyzed. Both evaluations identified problems with too complex architecture in one of the cases. For the content and design analysis, the overlay between the evaluation methods was again very strong. However, some issues were more specifically identified by heuristic evaluation. High bounce rate might indicate uninteresting content or unsuitable design. Nevertheless, without heuristic evaluation it is not possible to determine exactly what the problem is. Most relevant for this thesis was the evaluation of the purchasing process. Although Profesia.sk is not a traditional ecommerce website, multiple analogies can be found. The equivalent of a purchase in our case is sending a reaction to a job offer. We can then subsequently consider order conversion rate as the number of reactions sent, divided by the number of visits. Moreover, the paper also considered checkout completion rates metrics. For profesia.sk we can recognize checkout completion rate as the percentage of visitors who were able to finish the form for sending the CV to the company. Both heuristic and Google analytics evaluation confirmed major usability problems in the purchasing process. The problems were revealed using funnel reports. Funnels provide visual representation of conversion data between each step [31]. They then help to identify the exact page where the usability problem is. However, the usability assessment of purchasing was not done very thoroughly in this paper. Only general usability problems were found. It was not specified in detail what exactly the problem is and what could be the possible solution. Nevertheless, the paper proved that Google analytics can be used for finding usability issues and can achieve similar results than heuristic evaluation. On the other hand, the paper did not go further and did not specify the issues, nor did it contain any possible solutions. In this thesis, we will describe the usage of Google Analytics from discovery to proposal of the solution, implementation and evaluation of the results.

In conclusion, there are a great number of research papers dealing with usability. Basic usability principles have been the same for decades now. However, the discovery and analysis techniques have developed rapidly over recent years. With the development of big data technologies and cloud computing, the computation speed has rapidly increased, allowing the development of very effective web analytic tools. Although a great number of websites use Google Analytics, there is very little research done in the area of using this tool for improving usability.

2.3.3 Usability evaluation using heatmaps

Eye tracking is a technique where an individual's eye movements are measured, so that the researcher knows both where that person is looking at any given time and the sequence in which their eyes are shifting from one location to another [32]. Eye tracking techniques are commonly used for usability evaluation. The two main measurements are usually fixation and saccades. Fixations can be represented in multiple ways. Fixating on a single object on the website can mean that the object is interesting (i.e. a picture) or that it is too complex to be comprehended quickly. Saccades are quick eye movements occurring between fixations [32]. They can indicate confusion or difficulty in encoding the content. A paper by Ehmke [33] presented the results of an empirical study focused on analyzing the correlation between eye-tracking patterns and usability problems. There were a great number of usability problems which could not be revealed through eye-tracking only. These were problems such as small default font or the lack of an expected option. Nevertheless, eye tracking was successful in revealing problems such as missing functionality, misleading element, missing expected information etc. That proves that eye tracking is an effective way of finding usability problems. However, using eye-tracking can be too demanding considering the temporal, human, and financial resources. That is why cursor tracking techniques have been developed.

A study by Chen [34] analyzed the relationship between gaze position and cursor position during web browsing. The conducted research confirmed that there is a strong correlation between the eye and the cursor position. The distance between the cursor and the eye position was 290.5 pixels in average. Moreover, the previously mentioned paper by Huang [7] demonstrated that there is an especially high correlation on the search result pages. Since cursor tracking is significantly easier and cheaper, it can be used as a replacement for eye-tracking. In 2006, the paper by Arroyo [35] introduced the MouseTrack, a web logging system that tracks mouse movement on the website. The tool generated a visualization similar to a heatmap, which reflects the degree of activity in each area in the intensity of the shade. The visualization technique using heatmaps was derived from the fixation maps [36]. However, heatmaps visualize the level of observation intensity better.

Nowadays, there are multiple tools available that can be used for cursor tracking. Nevertheless, neither the tools nor the cursor tracking heatmaps are mentioned very often in scientific literature. Therefore, it is necessary to look for the information on the usage of heatmaps on expert blogs and in articles and especially in the documentation for specific tools. In this thesis, we will use the Hotjar tool to create heatmaps and user recordings. According to the Hotjar documentation [37], heatmaps can be used to uncover eight potential usability issues.

- Since heatmaps visualize clicks, it can be seen whether users clicked on the elements that are not links.
- Heatmaps can reveal if users are distracted from important content. Cursor activity should not be spread around the whole page, but rather focused on the important parts of the page.
- Users might be looking for information that is missing on the page. This can be revealed by the high scrolling percentage.
- Heatmap reports can also be used for uncovering potential unresponsiveness of the website.
- Users might not reach the bottom of the page because of false bottoms. A false bottom is a color block or a line break that can make the visitor think that they have reached the end of the page. With heatmaps, this problem can be easily identified.
- Heatmaps can also help identify if users are interacting with the important content on the webpage.
- Users decide whether to stay on the website or leave within a few seconds, after looking at the first few elements. Therefore, it is crucial to put the essential content on the top of the page, so that it is visible without scrolling. The Hotjar heatmap visualizes average fold position and therefore it is possible to classify the area in which the users should be engaged.
- Heatmaps visualize the activity around the navigation and the header area. Users should not spend too much time on navigation, since this would mean that they are distracted from the main content and they are unable to easily find what they want.

All these test cases will be further examined in this thesis.

There are a great number of both free and commercial tools for user behavior analysis. These tools can serve as a cheaper and more convenient alternative to typical user testing. Conducting user testing for finding usability issues has been a well-established method for decades. Using behavior analysis tools, on the other hand, is a rather new and not yet truly validated approach. The advantages considering resources used compared to user testing are undeniable. On the other hand, not enough scientific research has been done that would either confirm or deny the effectiveness of these tools for usability improvement.

2.4 Increasing conversion rate

As already mentioned in the introduction, the term conversion rate is usually used with the connection to an online purchase. Nevertheless, Jakob Nielsen in his article about conversion rate [5] mentions far more types of conversion events. Conversion events can be user registrations, signing up for a subscription, using a certain feature, downloading something etc. In other words, a conversion can be any key performance indicator (KPI). A key performance indicator is a measurable value that demonstrates how effectively a company is achieving its key business objectives [38]. One specific business objective for Profesia is to help people find jobs and help companies find employees. Therefore, in the context of this thesis, we consider sending a reaction to a job offer as a conversion. In an article by Norman [5], it is stated that one should try not to maximize the conversion rate but to optimize it. He supports this statement by an example of increasing the price of a product. If the price is increased by for example 5%, the conversion rate might decrease a little, but the revenue is higher and that is what is important for the business. That does not apply for the case analyzed in this thesis. Since the conversion is sending a reaction to a job offer, it always holds that the higher the conversion rate, the better for the company.

A paper by Moe [39] presents a model of conversion behavior consisting of six key components. Those components are numerically expressed and the resulting formula is then used for a calculation of the conversion behavior. The first component is *Baseline probability of purchasing*, which reflect to what extent the visits are purchase directed. The second one is *Positive visit effect on purchasing*, which means that the more a user visits the websites, the more probable it is that they will make a purchase. *Negative purchasing-threshold effect* on purchasing means that users that are new to the website are reluctant to share their personal information such as their credit card number or, in case of a job portal, a resume. *Heterogeneity in visit effects and purchase thresholds* takes into account the fact that not all customers are the same and therefore there is no general behavioral pattern. That depends heavily on the number of user groups. Profesia.sk has extremely high *Heterogeneity* since there are so many user groups based on age, region, level of education or skills. The next key component is *Evolving effects over time*, which expresses the situation when a user visits the website so often that they are no longer influenced by the content and are less likely to make a purchase. The last component is called *Hard-core never-buyers*. Those are the visitors who are using the website as an informational resource only. The paper further presents mathematical formulas for the components and applies them to the data supplied by Amazon.com. Even though the presented model is quite interesting, it is hardly applicable in practice. The resulting numbers of the model calculation are difficult to interpret and therefore they can hardly be used in everyday practice. Nevertheless, the paper is very informative in terms of analyzing the behavior of visitors and their reasons for converting or not converting.

Since the term conversion rate is relatively new, there are not many scientific papers on the topic. Nevertheless, conversion rates are a popular topic for online articles and expert blogs. [40] [41] [42] When dealing with conversion rates, analyzing the conversion funnel is a necessity. A conversion funnel is the path that a prospect takes through the website which ultimately results in a conversion. [45] In business and marketing, the term funnel is more connected to the general process of becoming a paying customer. There are various models, but the main stages are usually from building awareness, through developing interest and finally making a purchase. In the context of website analytics and ecommerce, the term conversion funnel is connected to the actual path within the website which the user takes before making a purchase. The path can lead for example from the Homepage through the Product Listing, Product Detail and Checkout. This path can be analyzed using Google Analytics. At every stage in the funnel, some users will drop off. Based on the percentage of users who left without proceeding to the next stage, possible room for improvement can be found. Users might be leaving because it is unclear what to do next, a registration is required, or there is something wrong with the design of the page [43]. Pages with high abandonment rate are good candidates for further improvement.

The analysis of the conversion funnel can only indicate the potential room for improvement. However, it is seldom helpful in actually identifying the problem and the analysis itself cannot increase the conversion rate. For finding the problems and their possible solutions a number of approaches are available. Statistics, stated in a paper by Chaffey [44], say that the most commonly used method for increasing conversion rates is A/B testing. A/B testing will also be used in our conducted experiments and will be described more deeply in the next chapter. Among other methods mentioned were for example the customer journey analysis, online surveys, customer feedback and usability testing. The paper also stated that many companies use Google Analytics and just look at the data without understanding why the numbers go up or down. Web analytics tools should have a clear purpose and scope set. They are great tools for optimizing web usage and they should not be used to keep statistics only. When used well, they can be a great source of information about users and their behavior.

To sum up, the term conversion rate in the context of ecommerce is a very popular topic of marketing and ecommerce expert articles and blogs. There are various methods for increasing the conversion rate. However, not all of them are also beneficial for the website usability. Email subscription popups are the most common example. Although popups are a very effective approach for gaining more email subscribers, they can be annoying for users and they can damage the overall user experience. Nevertheless, we believe that increasing the website usability should always lead to boosting the conversion rate. In this thesis we will try to support this hypothesis by performing a series of experiments.

CHAPTER 3

Methodology

In this chapter, we will describe the methodologies and processes used in this thesis. The experiments will be conducted in an iterative approach. After each iteration, the results will be evaluated and summed up. The next iteration will take into consideration the results of the previous experiments and therefore the information gained from the experience will be used. The goal is to achieve continuous improvement. One iteration consists of five phases: Finding usability issues, Proposing solutions, Ranking the solutions, A/B testing, Evaluation of the results. Each of these phases is described in more detail in this chapter, including which tools will be used and how. Lastly, we will combine the results of all the experiments and draw a conclusion considering the relationship between usability and conversion rate.

3.1 Finding usability issues

We will use data from various sources to find possible usability issues. First of all, we will use data from Google Analytics and Hotjar tools. Furthermore, data from the customer support service will be utilized. Last but not least, the information from the Net Promoter Score will be analyzed. The Net Promoter Score (NPSs) is one of the simplest customer satisfaction and loyalty measures, which asks customers only one question with a 0 to 10 rating scale: „How likely is it that you would recommend our company to a friend or a colleague?“ [45]. Apart from rating the website, users can also send their feedback on the website. The visitors are divided based on their rating into 3 groups: the detractors (rating 0-6), the passives (7-8) and the promoters (9-10). The Net Promoter score is then calculated based on the following formula:

$$\frac{number\,of\,promoters - number\,of\,detractors}{number\,of\,respondents} \times 100 \tag{3.1}$$

The data from all of these sources will be used to create a set of potential usability problems.

3.1.1 Using Google Analytics for identifying usability issues

Google Analytics was launched by Google in 2005. Since then, the tool has completely changed web analytics. Because it is easily understandable, it has made web analytics accessible to almost anyone and not only to IT specialists and analysts. There are many definitions of web analytics. A book by Cutroni [46] claims that web analytics should consist of three main tasks: measuring qualitative and quantitative data, continuously improving the website, and aligning the measurement strategy with the business strategy. In this whole process, Google Analytics can only collect quantitative data. The data basically tell us what happened on the website and where the website traffic comes from. Apart from tracking many standard website metrics such as pageviews, visits, bounce rate, unique visitors etc., Google Analytics can also track custom goals or the whole ecommerce purchase process. Moreover, it provides segmentation tools, which allow one to divide the traffic and look deeper into the specific groups of users. Even though these data are a critical part of web analytics, the qualitative data also have to be collected through online surveys and other behavior analysis tools.

Before starting with Google Analytics, an account has to be created. The account can have multiple *properties*. In a *property*, data from a website are collected through a unique tracking code. If a single person is running multiple websites, they have a *property* for each of these websites on their profile, so that the data from different websites are not mixed together. Each *property* can have multiple *views*, which is an access point for data reporting. Different *views* can be used with various settings to provide particular types of information. The data is collected through page tags. A page tag is a small piece of JavaScript that must be placed on the websites that we want to track. The tag contains the tracking code and as the users' browser processes the data from the website it contacts Google Analytics servers. The information is then sent to the *property* and can be displayed through the *views*.

One of the *properties* used for the usability analysis will be the *clickstream property*. *Clickstream property* is set up to provide information about the sequence of pages. By default, a pageview is assigned a specific url. However, when we want to gain information about the path which users take while navigating the site, the specific url is irrelevant. Using regular expressions and filtering, the urls are grouped together according to their content. For example, we group all pageviews of details of job offers to one group called *offerdetail* and all views of application forms to a group called *send_cv*. The specific urls containing parameters and other case specific information are unimportant for us since we want to analyze general behavior of all users. By having the addresses grouped together, we can analyze how many percent of the users proceed from the offer detail to the application form. This can give us an overview of general behavioral patterns. *Clickstream property* enables us to create funnels for further analysis.

Before sending an application to a job offer, each user has to take a series of steps. Funnels represent this path. They give us a visual representation between each step. We can see the number of drop-offs and also the percentage of users continuing to the next step. This information can be used to find potential usability issues. When one step of the funnel has a high drop off rate, it can indicate that the users are confused and do not know how to continue. It can also mean that they are scared of the outcome, there is missing information, or just too many other options. By identifying the problem, the specific webpage can be improved and the conversions will increase. In our case, the default funnel which will be analyzed consists of the search results page (also called *listing*), the offer detail page and the application form. For analyzing the users who continue in the funnel we will use the term *click-through rate* (CTR). Even though the term is usually associated with marketing and web advertisement, it can also be defined as the percentage of people who click on an element that they have been exposed to [47]. If, for example, 90% of people continue from the listing to the offer detail, we say that the click-through rate (CTR) between listing and offer detail is 90%. It is important to remember that the closer to the end of the funnel, the more important the CTR is. If the CTR of the application form page is increased, it must necessarily lead to more applications sent and therefore to a higher conversion rate, since the application form page is the very last step in the funnel. However, when the CTR is increased earlier in the funnel, it can still lead to more drop-offs later in the funnel and may not necessarily lead to proportionally raised conversions. To sum up, funnels are an important part of the analysis, since they reveal which subpages in the application process cause problems for most users.

Another feature of Google Analytics which will be used often is segmentation. Segments enable us to analyze only certain group of users. Different groups of users can have different behavior patterns and they should sometimes be treated separately. We assume that there will be a considerable difference between the behavior of logged-in users compared with that of non-logged-in users. We assume that users who are already logged in are more familiar with the website. Non-logged-in users, on the other hand, might have usability problems with tasks which are easy for logged-in users. Segmentation will also be used when dividing the traffic according to the device used. A page which is straightforward for desktop users can cause usability problems for mobile phone users. Last but not least, segmentation will be used for evaluating the results of A/B tests. More about evaluating the A/B tests will be described in A/B testing subhead.

One way of identifying that a reaction to a job offer has been sent is to use Google Analytics goals. A goal represents a completed activity. Within the website, multiple goals can be defined. A goal can, for example, be a completed registration, subscribing to a newsletter or sending a reaction to a job offer. However, Google Analytics only counts one goal completion per session for each goal. That means that a user can complete two different goals within the same session. However, they cannot complete the same goal multiple times. Therefore, if a user sent a reaction to more jobs, Google Analytics would only count it as one goal completion. That is why we will use the enhanced ecommerce plug-in. The enhanced ecommerce plug-in enables the measurement of user interactions with products on ecommerce websites across the user's shopping experience, including: product view in listing, product clicks, viewing product details, adding a product to the shopping cart, the checkout process and transactions [48]. Even though profesia.sk is not a typical ecommerce website, we can create an analogy to an e-shop and use the plug-in to track the behavior of users in the process of sending a reaction to a job offer. We will consider a job offer as a product, while adding the product to the shopping cart and the checkout process will be the equivalent of opening an application form. The transaction will be the actual sending of the job application. Therefore, the main metric for evaluating the experiments will be the number of transactions made. Through an analysis of the product list performance we can find room for usability improvements in the search process. The performance of different listings on the website can be measured by collecting information about the number of products which appeared in the listing, the number of clicks, transactions etc. It holds that the higher the position of a job offer in the listing, the more views the job offer detail should get. If this does not apply, it means that the usability of the search is not ideal, since the user should be shown the most relevant result first. In conclusion, by creating an analogy to an ecommerce website, we can acquire data that are more precise and therefore more effective in analyzing website usability.

Except for the already mentioned metrics and methods, other useful Google Analytics features, such as the bounce rate, average time on page, visitor acquisition data and campaign tracking will be used when necessary. Even though Google Analytics is very effective in collecting and visualizing data, it can only provide hints on where to optimize. It cannot be used to specify the actual problem. However, it is extremely important in providing the necessary input on general behavior patterns. In addition, the main usage of Google Analytics in this thesis is in the measuring of the effect of the usability improvements on the conversion rate.

3.1.2 Using Hotjar for finding usability issues

Since Google Analytics can collect quantitative data only, we will use the Hotjar tool for collecting qualitative data. Hotjar is a commercial analytics tool offering features like heatmaps, visitor recordings, conversion funnels, form analysis, feedback polls and surveys. The Hotjar tool works through inserting a piece of script on the webpage which we wish to track. The data from the page are then saved to the Hotjar account where it can be analyzed. Since we don't want to make a lot of modifications to the code of the website, we will use Google Tag Manager to insert the data. Google Tag Manager is a tag management system that allows you to quickly and easily update tags and code snippets on a website. A tag is a snippet of code that sends information to a third party such as Google or Hotjar [49]. We will use Hotjar mainly for heatmaps, visitor recordings and surveys.

A heatmap in Hotjar visualizes the movement of a cursor, clicks, taps and scrolling behavior. It reveals which parts of the website are important for the users but also the areas which they barely notice. Moreover, attention should not be spread around the webpage but rather focused on the essential content. The part of the heatmap is the page fold visualization. The page fold is an abstract horizontal line dividing the webpage.

The content above the fold can be seen without any interaction. According to Nielsen [50] web users spend 80% of their time looking at information above the page fold. Even when they do scroll down, they allocate only 20% of their attention below the fold. That is why all the important content should be above the fold. The problem with the page fold gets even more significant with the increasing use of mobile devices. Moreover, by determining where the cursor stopped, we can determine which elements caught the users' attention and made them think. Ultimately, the heatmaps will be used to visualize which areas of the webpage are getting the most attention.

The second feature of Hotjar which we will use for usability analysis is visitor recordings. By recording the behavior of users, we can notice patterns in their action which might uncover potential usability issues. Since it is not possible to watch recordings of all visitors on all subpages, we will only choose a sample group of users on specific pages. We will mostly examine the process from the search result page, through the job detail view to sending an application form. We might see which parts of this process are the most confusing for the users. We will also be able to see how users are using the search on the webpage and how long it takes them to find the information they are looking for. On the job detail subpage, we will analyze the reasons why users continue to the application form or why they leave the job detail and go back to the search. This analysis can reveal what the most important piece of information for the users is. By analyzing visitor recordings, we can actually put ourselves in the place of a job seeker and therefore understand them better.

Lastly, we will use Hotjar for conducting surveys. We will put surveys on specific subpages which we consider the most problematic. A survey can contain single choice, multiple choice, long or short text questions. We will mostly use closed answer questions since they can be more easily evaluated compared to open questions. Apart from specifying the page on which the survey appears, we can also determine the action which triggers the survey. By providing a survey just before the user leaves the website, we can discover their objectives and concerns. Although web surveys are an excellent way of targeting large groups of users very easily, they often exhibit a low response rate of around 10-25% [51]. Since we do not want to disturb users too often, we will only use surveys sparingly.

Hotjar is an extremely useful tool for collecting qualitative data. It can be considered a cheaper and more comfortable alternative to typical user testing. Although there is no real contact with the users, their behavior can be analyzed using heatmaps and recordings and their opinions and objectives can be gathered using surveys.

3.1.3 Using other sources for finding usability issues

Apart from collecting quantitative data from Google Analytics and qualitative data from Hotjar, we will also use other available sources of user feedback. Firstly, we will use data from the previously mentioned Net Promoter Score. Apart from providing the exact value of the score, there is a possibility to leave textual feedback on the website. Even though not all the feedback is connected with usability issues, often there are suggestion for improvement which are very beneficial for our process. Moreover, we expect that with every usability improvement, the Net Promoter Score will rise.

Another source of suggestions for usability improvements is the customer support department. Apart from providing the support on phone and email, profesia.sk also uses LiveAgent[1] help desk software. The chatting button is available on almost every subpage. When users are confused about how to continue they can always contact the customer support service which helps them to proceed. Therefore, employees from the customer support department have a very good overview of what causes the most problems for the users.

3.2 Proposing solutions

After identifying the specific usability problem, a set of solutions will be proposed. Firstly, we will try to discover why the problem occurs. We will also analyze for which group of users the problem appears. In some cases, there might be a problem with the responsiveness and it might cause problems only for users on mobile devices. Later, we will conduct research using scientific literature and various online sources and try to find similar cases which have been successfully solved. After analyzing the current situation, we will create numerous hypotheses about the problem solution. The hypotheses will be in the following format: If [action] then [outcome] because [reason]. An example of a hypothesis could be: "If we make the application form shorter then more users will send an application because they will be less discouraged by a long and laborious form." By creating a hypothesis first, we can look at the problem from a broader perspective. When we explicitly name the problem and the expected outcome, we can create a set of specific solutions. We can suggest multiple solutions for each hypothesis. The solution description should specifically describe what the changes will be and how we want to track whether the improvements have been successful. In summary, the process of proposing solutions consists of analyzing when, for whom and why the problem occurs. After further analysis, various hypotheses will be proposed. For each hypothesis, there will be at least one solution offered.

3.3 Ranking the solutions

In this phase of the process, we have found the usability problem and we have a set of proposed solutions. Next, we need to decide which solution to implement. Before the decision, we need to rank the proposed solutions first. For the ranking, we will use the PIE ranking model [52]. Each solution will be ranked based on three criteria: potential, importance, and ease of implementation. Potential takes into consideration how much improvement can be made on the webpage. If the webpage causes no problems for users and there is a low drop-off percentage, it means that there is little room for possible improvement. Even if some improvements were made they would not have a great impact

[1] https://www.ladesk.com/

on the overall usability experience or conversion rate. Importance measures the traffic on the page. In the case of low traffic on the given subpage, the usability issues on the given page have lower importance. Lastly, we need to consider also the ease of implementation. We need to consider the invested time and resources. Moreover, we also need to take into account the technical, organizational and „political“ factors. Every solution can be given a maximum of ten points for every criterion. The solution with the highest count will be implemented in the given iteration. The other solutions will be kept and considered again in the next iterations.

3.4 A/B testing

For actually testing the solution we will use the A/B testing method. A/B testing is the most commonly used method for increasing conversion rates [44]. It is the simplest form of controlled experiment. The testing is conducted with actual data, when users are randomly divided into two halves. While one group of users sees version A of the page, the other group sees version B. Based on Overall Evaluation Criterion (OEC), it is then decided which version is better. In this thesis the overall evaluation criteria are improving the usability and improving the conversion rate. The main advantage of A/B testing is the fact that both versions of the website have exactly the same conditions and therefore their performance can be objectively compared. We could use no testing at all and just publish the changes that were made and observe whether the conversion rates have increased. However, even if the conversion rate increased, we could not be sure if it was caused by changes made by us or just by some external factors such as seasonality. With A/B testing, we compare the old version of the website with the new version at the same time and compare the conversion rates of version A and version B.

According to Reeve [53], A/B testing is probably one of the most well-known experimental approaches to user experience and interface design. One of the leading experts on A/B testing is Ron Kohavi, a Microsoft Distinguished Engineer and General Manager of the Analysis and Experimentation team at Microsoft's Artificial Intelligence and Research group. According to his presentation at the KDD 2015 conference [54], Microsoft conducted about 300 experiments on the Bing search engine every week. That basically means, that there is no single Bing, since a user is exposed to 15 concurrent experiments. Not only Microsoft, but many other successful companies such as Amazon, Netflix or eBay are running thousands of A/B tests a year [55]. Controlled experiments are an excellent way to truly prove the hypothesis, which we proposed earlier in the process.

Before conducting an A/B test, we have to be aware that not all subpages of the website are suitable for testing. For us to be able to evaluate an A/B test, we have to first ensure that the statistical power of the test is high enough. The statistical power is the likelihood that an experiment will detect an effect where there is an effect to be detected [56]. The power is influenced by factors such as sample size, effect size and significance level. By having a large sample size we can be more confident that the results are the consequence of our test and not a just a random chance. For example, if we conduct a test on 10 people, it means that 5 people see each version. However, we would never be able to evaluate the test because it can easily happen that the 5 people seeing version B are just more determined to apply for a job and they would apply even if they saw version A. However, if we conduct the experiment on 10,000 visitors and the number for version B is considerably higher than that for version A, there is a low probability that it is a coincidence. Moreover, the statistical power also takes into consideration the value of expected conversions and the expected uplift. For instance, we can have a subpage with 100 expected conversions and we would like to increase the conversions by 1%. This means that we expect that version A will have 100 conversions and version B 101. This test would have very low statistical power since the required uplift is so low that it can also be a coincidence that there is one more conversion in version A compared to version B. As can be seen from the given examples, statistical power depends heavily on having a large sample size and a number of conversions. That is why A/B testing is only suitable for webpages which have enough pageviews. Since profesia.sk has around 10 million pageviews weekly, it creates a perfect environment for conducting a lot of A/B tests. We will only conduct tests with a power higher than 80%. This means that with respect to each test we can say with at least 80% certainty that if there is an effect to be detected, our experiment will detect it. For the calculations we will use the free online tool A/B testing calculator by Online Dialogue[2].

When we make sure that we will be able to evaluate the test, we can actually start by creating the test. For the A/B testing we will use the previously mentioned Google Tag Manager (GTM). We will use the open source GTM testing library[3] created by Jorrin Quest. The library is simply added to the GTM and no installation is required. The test is created by adding a custom HTML tag to a given subpage. The tag contains a piece of JavaScript which will manipulate the elements on the website and make the changes for version B. In the case that the test requires some information from the backend, it is passed to the frontend in the data layer variable. A data layer is an object that contains all the information that you want to pass to Google Tag Manager [57]. Once we have the B version of the website prepared, we only need to set up the parameters for the GTM testing library. The library splits the visitors into two halves and saves the information about the version of the experiment which was displayed to them in the cookie of each user. In the case that the user has already visited the website, the same version of the experiment will be displayed, according to the cookie saved in their browser. Every time the subpage on which the experiment is conducted is displayed, an *event* is sent to Google Analytics, carrying information about which version was displayed. Google Analytics *events* are user interactions with content that can be tracked independently from a webpage or a screen load [58]. Each *event* has fields for category, action, label and value. Events sent for A/B tests will be assigned the category „AB-test“ and the action „[Test ID]: [Name of test] – [Control loaded/Variation loaded]“. Control is a conventional name for version A and variation is the term for version B. If the event action will be Control loaded that will indicate that the user was shown version A. Except for sending

[2]https://abtestguide.com/calc/

[3]https://abtestguide.com/gtmtesting/

an event on loading the experiment, we can also send custom events on actions which we are interested in, for example when a user starts filling out a form.

Although, the user should be shown the same version every time they visit the website, there is always the possibility that they will see the other version as well, for example if they delete the cookies or use a different browser or device. These situations cannot be avoided and they are called sample pollution. The longer we run the test, the higher the sample pollution gets. That is why we want to run the test only for a specific time period. Each test should run for at least a week, because there are great changes in user behavior according to the day of the week. On the other hand, to avoid high sample pollution we will not run tests for longer than 4 weeks. We want to let every test run for full weeks, meaning that we will not stop the experiment after a week and a half. The main objective for stopping the experiment is reaching the sample size for achieving a satisfactory power and confidence level. We have already discussed the statistical power of the experiment and we will describe the confidence level in the next paragraph.

Confidence intervals represent the amount of error allowed in A/B testing [59]. We use the intervals to mitigate the risk of sampling error. Moreover, they express the confidence in the test results and the fact that the difference between the versions is not by chance. The acceptable confidence level is usually around 95%, however, it depends on the person conducting the test how much risk they are willing to take. Setting the confidence level to 95% would mean that if we were 95% or more confident that version B will perform better than version A, we would implement version B as a permanent solution. For the confidence level calculations we will use the Bayesian A/B test calculator[4]. Based on the number of users and number of conversions for each version, the calculator returns the probability of version B outperforming version A and vice versa. We will consider the acceptable confidence level for each experiment individually.

The two most commonly used approaches for evaluating the experiments are the frequentist approach (also known as t-testing) and the Bayesian approach. The differences between these two approaches are described in a document by Online Dialogue [60]. In the frequentist approach, the basic assumption is that there is no difference in the conversions of versions A and B. Using the t-test, we try to reject this hypothesis and prove that B outperforms A with a set probability (usually around 90 or 95 %). Generally, the Bayesian approach is considered to be more easily understandable. Based on the test results, the probability that B outperforms A is calculated. That means that there is no binary outcome but the decision whether the test was successful depends on the risk that we are willing to take. In general, the Bayesian approach is considered to be easier to understand and more business-driven. Consider a simple example, where the p-values of a frequentist test was 0.139. Based on a confidence level of 90%, the test would be considered as unsuccessful because version B is not significantly better than version A (the p-value is higher than the cut-off value of 0.1). Using the Bayesian approach to evaluate the same test gives us the probability of B outperforming A as

[4] https://abtestguide.com/bayesian/

86.1%. Afterwards, a simple risk analysis can be done, where possible gains in revenue are compared to losses and a decision is made. According to Online dialogue this leads to more successful experiments and higher revenues. The Bayesian approach makes the results of the experiment more understandable even for people who are not familiar with A/B testing statistics.

Although the concept of A/B testing is quite easily understandable, performing the experiment correctly can be challenging. Most of the experiments which we will perform will not be difficult to implement. However, the pre-analysis and also the evaluation of the results will be extremely critical.

3.5 Evaluation of the results

The actual data from the experiment will be gained from Google Analytics. Using segmentation, we will divide the users into two segments: Users who sent an event that version A was loaded and users who sent an event that version B was loaded. Afterwards, we can analyze these segments and we can compare the number of conversions or the number of users who continued in the conversion funnel. Moreover, we can create smaller segments, according to a device type or according to whether the user was logged in. We can then see that even if version B did not perform better in general, it might, for instance, be better for users on a mobile device. After analyzing the data from Google Analytics, we can enter the data to the previously mentioned Bayesian calculator and calculate the probability that version B will perform better than the original version.

Apart from considering the quantitative data from Google Analytics, we will also examine the qualitative data and the effect of the changes on usability. We will use the same sources which were used for the usability analysis (customer support feedback, Hotjar, Net Promoter Score etc.) and try to evaluate whether the solution which was tested actually improved the usability. However, the tools which collect qualitative data cannot collect the data based on the version which was displayed. That means that the Hotjar tool is not able to make recordings or heatmaps for version B only. The same applies for Net Promoter Score tool. The score is calculated for the overall experience on the website, it cannot be directed specifically to a tested subpage. The NPS is calculated based on a simple question: "How likely is it that you would recommend our company to a friend or a colleague?" We do not expect that running the experiments will have such a strong impact that it would significantly shift the NPS score. That means that we will most probably not be able to detect the effect on usability during the testing. Moreover, both the feedback from the customer support department and the NPS score are calculated for all users together and cannot be divided based on the version of the website which was displayed, i.e. there is not an NPS score for users with version A and users with version B, there is only one overall NPS score. That is why it will be difficult to assess the difference in usability between versions A and B. Nevertheless, we will monitor overall values and pay attention to possible deviations. Furthermore, we expect that after running multiple successful experiments and implementing several small improvements, the Net Promoter Score should rise over time.

Later we will need to make a decision on whether we will implement version B for all the traffic on the website. This decision will be based on the quantitative data on the conversion rate and the qualitative data on usability. The main objective of the experiment will be to improve usability. However, usability can hardly be measured and therefore it will be difficult for us to determine if version B actually improved the usability of the website. We can only make an educated guess based on the data available. The actual effect on usability will be better measurable after version B has been implemented for all the traffic. On the other hand, the effect on the conversion rate is clear, based on the data from Google Analytics. We will make the decision whether to implement version B by combining the information about the effect on the usability and the conversion rate. That means that, for example, if we believe that version B dramatically improves usability but there is only a 70% chance that it will have a better conversion rate than version A, we will publish version B for all the traffic. If, on the other hand, we realize that version B will not make any significant changes in the website usability and the probability that the conversion rate will increase is not exceptionally high, we will keep the default version. In conclusion, apart from considering the data on the conversion rate, the decision will be heavily based on the confidence that the solution actually improves the usability.

The very last step of the iterative process is the reflection on the experiment. First, we will analyze the procedure. We will determine whether the experiment brought the expected results and whether the entire process went according to expectations. Moreover, we will detect whether our hypothesis was correct. However, we will not use a single experiment in confirming or disproving a hypothesis. We will not assess the hypothesis until we run multiple tests on it. When we have conducted at least two independent experiments for the same hypothesis that are both negative, we will be able to say that our hypothesis was not correct. Nevertheless, each hypothesis, whether it is confirmed or disproven, makes us understand our users better. Not only will we analyze the past iteration, we will also reflect on the gained knowledge in the future process. By learning from experience, we expect that over time the number of successful experiments will rise.

3.6 Drawing a conclusion

The main objective of this thesis is to analyze the relationship between usability and conversion rate. The goal of each experiment is firstly to improve the website usability and secondly to increase the conversion rate. Each iteration of the process will provide us with a piece of information on the relationship between improving usability and raising the conversion rate. The final step, after the last experiment has been evaluated, will be to summarize the gained knowledge. We will firstly analyze if we were successful in advancing the usability of the website. We expect that after the whole process is finished, the Net Promoter Score should be higher than it was at the beginning. Our assumption is that if we succeed in improving the website usability, the conversion rate will also rise. Nevertheless, we also expect that not all the improvements will have a positive effect on the conversion rate. In this phase of the process we want to determine what the effect of various usability improvements is on the conversion rate. Additionally, we will analyze the overall results for different user groups. It is possible that increasing usability will only have a positive effect on the conversion rate of a certain group of users. In conclusion, in this last step of the process we will join the results from all the iterations and we will form a statement on the relationship between usability and conversion rate.

CHAPTER 4

Results

In this chapter, we will describe the experiments which we did in order to determine if increased usability leads to a higher conversion rate. We conducted all the experiments on the job search portal profesia.sk. Since there are around 100,000 users who visit profesia.sk daily, all the experiments needed to be carefully tested before they were released. As already mentioned in the Methodology chapter, the experiments were done iteratively. The order in which the experiments are stated in this thesis does not necessarily reflect the order in which the experiments were conducted. In order to be able to evaluate the experiments easily, we decided not to run two experiments simultaneously within one page. Running two A/B tests on the same page at the same time results in having four possible versions of a single page and we would need to evaluate each of these versions separately. Furthermore, the experiments would need to run for longer periods, since the traffic per version would not be so high, because the traffic would be split into quarters instead of only halves. This is why we always ran only one experiment at a time on a single page. We ran most of the experiments on all of the traffic. However, there were some experiments which were run only on traffic from desktop devices. Moreover, experiments which displayed some new text were usually done for the Slovak version of the site only. This was due to the fact that the translation process was laborious and the number of users using other language versions of the website was essentially negligible. We also need to stress the fact that all the statistics in this thesis are calculated per user. This means that, for example, if we say that the conversion rate of an application form is 80%, we mean that from all the users who visited the application form, 80% also sent a reaction. This should not be mistaken for the total count of events, i.e. it does not mean that in 80% of cases, if the application form was displayed, a reaction was sent.

The statistics described in this chapter such as the number of visitors and conversions per version were acquired using Google Analytics. As already mentioned in the Methodology chapter, when a user is shown version A or B, a piece of information (called *event*) is sent to Google Analytics. The number of visitors per version is then counted as the number of users who sent an *event* that version A/B was loaded. The number of visitors with conversion is counted as the number of users who sent an *event* that version A/B was loaded and sent a reaction afterwards. The percentage chance that one of the versions is better than the other was then calculated using the Bayesian calculator by Online dialogue [1].

All the experiments were done by the Optimization team of Profesia.sk. The team consisted of four members:

1. **Team leader (Veronika Vidová):** Responsible for managing the team, organizing meetings, writing reports, overlooking the whole experiment lifetime process etc.
2. **UX designer (Ferenc Viola):** Responsible for the graphic design of new elements, creating user surveys, proposing usability improvements, copywriting etc.
3. **Backend developer (Michal Gallovič):** Responsible for developing experiments which require modifications in backend code.
4. **Frontend developer, analyst (Katarína Smolíková):** Responsible for developing experiments which require modifications in frontend code only (experiments were implemented through Google Tag Manager), pre-analysis for the experiments, analysis of the results of experiments (through Google Analytics).

The experiments proposed in this thesis were the results of team discussions during weekly meetings.

The chapter is divided into three parts. First, we will describe the experiments conducted on the application form page. We have decided to separate these experiments into an individual section, since we did many experiments on this page and, as will be later explained, these experiments yielded different results than the experiments conducted on the remaining pages. Secondly, we will describe the experiments conducted on various other pages. We will not only illustrate how the experiments were carried out, we will depict the whole process including finding usability issues, proposing solutions, ranking the solutions, conducting an A/B test, evaluating the results, and drawing conclusions.

4.1 Experiments conducted on the application form page

As the very first step of usability analysis, we defined the path which users need to go through before sending a job application. The path we considered consisted of the homepage, the listing page, the detail of a job offer, the application form, and the page after the application has been sent, which is also called a *thank-you page*. Naturally, not all the conversions needed to follow this path exactly. For example, a user can access

[1] https://abtestguide.com/bayesian/

the detail of a job offer directly from a search engine, through a direct link, or from recommended job offers which are sent daily by email. The presented path represented the conversion funnel for the majority of users. We used Google Analytics to determine the percentage of users who drop off the funnel in every step. The resulting numbers were as follows:

- **Homepage to listing:** 10% users drop off
- **Listing to detail of a job offer:** 28% of users drop off
- **Detail of a job offer to application form:** 82% of users drop off
- **Application form to thank-you page:** 42% of users drop off

According to these statistics, it might seem that the biggest room for improvement is in the detail of a job offer. However, the high drop off number can also be caused by poor search performance or the quality of the content of job offers. A high drop-off can be the result of bad search performance because it indicates that users opened a number of offer details but were not able to find one which would be suitable for them. Although increasing the search performance would definitely increase both usability and the conversion rate, the modifications needed would be too demanding for the scope of this thesis. Secondly, the high drop-off rate is caused by the quality of the job offers, which is something that can hardly be influenced by profesia.sk. However, we considered the drop-off on the application form page to be relatively high. The button displayed in the offer detail which leads to the application form is labeled *Send a CV to the company*. Therefore, we expected that the users who click on this button are already committed to send the application. That is why we believed that a 42% drop-off rate from the application form is too high and indicates possible usability issues in the application form. Moreover, lowering the drop-off rate of the application form will definitely lead to an increased conversion rate, since the transition from the application form to the thank-you page is the very last step in the funnel. If we decreased the drop-off rate of, for example, the homepage, it might not necessarily mean that the conversion rate would rise, since users might drop off later in the funnel. Based on this analysis, we believed that the experiments conducted on the application form page would increase the conversion rate.

After this analysis we were positive that there has to be a usability issue in the application form. We proceeded with the second step of our framework which is Proposing solutions. Various hypotheses were created during team meetings. Here are a few examples of such hypotheses:

- **H1:** If we make filling out the form easier for the users, more people will send an application because they will not be discouraged by the effort needed to complete the form.
- **H2:** If we inform users on what will happen after the application has been sent, more users will finish the application form because they will know what to expect.

- **H3:** If we award users with positive feedback, more people will finish the application form because they will be notified that they are proceeding well.

A few more hypotheses were proposed and for each of the hypotheses a set of solutions was proposed. Afterwards, the solutions were ranked based on the previously mentioned PIE ranking model. We assigned every solution one to ten points for potential, impact and ease of implementation. Since the impact is connected to the traffic on the page, the value was the same for all of the solutions proposed on the application form page. We assigned each solution with the potential, based on our belief that the solution would actually improve usability. After the solutions were ranked, we ran an experiment for the solutions with the highest ranking. Rather than naming all the experiments which we ran, we decided to describe the most interesting ones in more detail.

Before running any experiments on the application form page we had to calculate how long we needed to run the tests for in order to get reliable results. For the application form, there are on average 30,000 unique visitors per week. The conversion rate of the form is 58%. We wanted to run the test with both a power and confidence level of 95%. For the test duration calculation we used the AB Testguide calculator by Online dialogue [2]. The calculator showed that in order to detect an increase in the conversion rate of 2 and more percent, we only needed to run the test for one week. However, if we wanted to run the experiment for a certain group of users only, or if we wanted to detect the improvement for a specific device, we needed to run the experiment for longer, since splitting the traffic into more groups would decrease the sample size.

4.1.1 Modifying the captions of the upload buttons

When trying to improve the usability of the application form, we first analyzed if all the fields and their captions were understandable. There were three upload buttons in the application form: for uploading a CV, a cover letter and other attachments. We noticed that all of these buttons looked exactly the same and therefore could easily be mistaken. Before, they had exactly the same caption: *Select*. We decided to add information to each of the buttons, stating what exactly should be uploaded using each of them. Therefore, the buttons were labeled: *Select CV, Select the cover letter, Select another attachment*. We believed that the form would be more understandable. Since we wanted to keep the implementation as simple as possible, we decided to run this test only for users using the Slovak version of the website. Otherwise, we ran this experiment on all devices for one week. The experiment required only frontend changes and was developed through a simple JavaScript code, which was inserted into the website using Google Tag Manager. The difference between versions can be seen in figure 4.1.

[2] https://abtestguide.com/abtestsize/

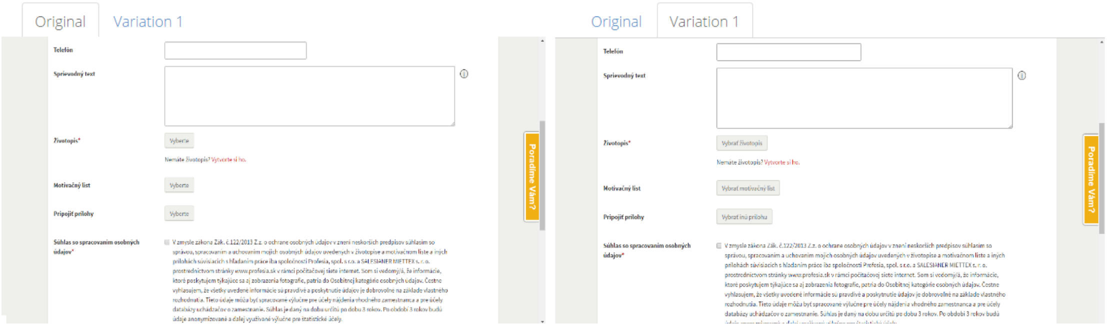

Figure 4.1: Modifying the captions of the upload buttons experiment

Table 4.1: Experiment results: Modifying the captions of the upload buttons

	Unique Visitors	Conversions	CR	CR difference	Chance of being better
Vs A	13629	7825	58.23%		
Vs B	13771	8196	59.51%	3.66%	100%

Experiment results

We were confident that version B would improve the usability and therefore we were determined to implement it. Nevertheless, we tested it first in order to determine the effect on the conversion rate and to make sure that the effect was not negative. The experiment proved that labelling the buttons with clear descriptions led to a higher conversion rate. The statistics for the experiment are stated in the table 4.1. To calculate the chance that version B is better than version A we used the Bayesian calculator by Online dialogue. [3]. Version B not only produced more conversions, but the difference in the conversion rates was so high that we could say with 100% confidence that version B was better. Therefore, we decided to implement version B for all traffic and all language versions. We can also say that usability was improved, since, after implementing the solution, the Net Promoter Score for Profesia.sk rose from 40.23 by 8,5% to 43.68. Although it cannot be proven that this increase was caused by changing the button captions in the application form, it might have contributed. Ultimately, the experiment was successful and it supported our hypothesis that making the form more understandable and simple would increase the conversion rate.

4.1.2 Removing the academic degree input

The next experiment we tried was focused on testing hypothesis H1: "If we make filling out the form easier for the users, more people will send an application because they will not be discouraged by the effort needed to complete the form." When trying to increase the conversion rate of a form, one of the first things to consider is the laboriousness of the form. Typically, the less input fields the form has, the better the conversion rate. That

[3] https://abtestguide.com/bayesian/

Table 4.2: Experiment results: Removing the academic degree input

	Unique Visitors	Conversions	CR	CR difference	Chance of being better
Vs A	14965	8718	58.26%		
Vs B	15112	8769	58.03%	-0.39%	34.5%

is why we decided to remove all the inputs which were not necessary. At first, we started with removing the input field for academic degree. Our assumption was that the field can appear discouraging for people with no academic degree. Moreover, the information about the degree should be written in the CV and therefore it is not necessary to write it in the application form as well. The main reason that we decided to implement this experiment as one of the first experiments was the fact that the difficulty of the implementation was very low and we believed that reducing duplicitous information would improve the usability of the website. The experiment was developed through a piece of JavaScript code inserted via Google Tag Manager. We ran this experiment on all traffic for one week.

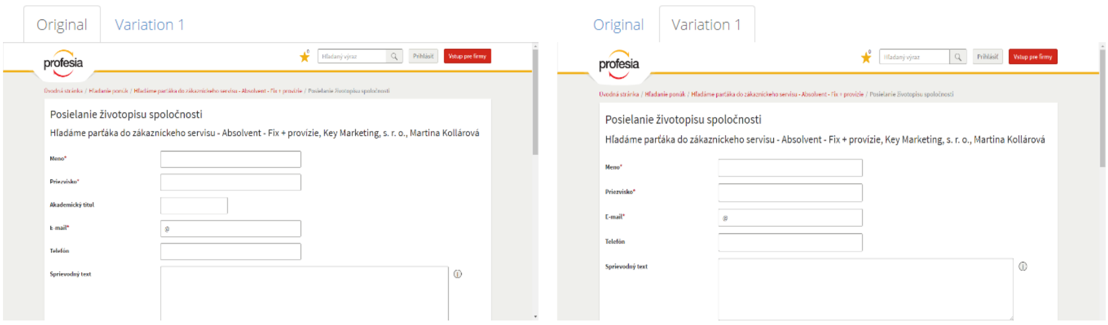

Figure 4.2: Removing the academic degree input experiment

Experiment results

The results of this experiment showed no significant difference between the two versions. The specific statistics can be seen in the table 4.2. Although version B has a lower conversion rate than version A, it is not significantly worse. Moreover, since this was the first test we conducted for the hypothesis H1, we did not consider this hypothesis to be disproven yet. This experiment was probably unsuccessful due to the fact that the academic degree is not a problematic field for users. Therefore, we decided not to implement version B on all traffic and after stopping the experiment, we left the academic degree field in the application form.

4.1.3 Removing the cover letter

Although the first experiment for H1 was not successful, we were confident that there were still ways to simplify the application form. As already mentioned, in the application

Table 4.3: Experiment results: Removing the cover letter

	Unique Visitors	Conversions	CR	CR difference	Chance of being better
Vs A	15621	9096	58.23%		
Vs B	15330	8979	58.57%	0.58%	72.8%

form there were three upload buttons: for uploading a CV, a cover letter and other attachments. Removing the button for other attachments was not possible, since some companies require the applicants to solve some additional tasks as part of the application. Moreover, it would be very difficult to join all the attachments into a single button due to other external HR systems which are connected to the website. Therefore, we decided to remove the upload button for a cover letter. A cover letter was not a required document in the application form. Furthermore, we assumed that for job offers for lower-level positions, it was unnecessary for the companies to demand a cover letter. We also believed that when users see the upload button for a cover letter, they just assume that it is a compulsory field and therefore are discouraged to continue if they do not have one. On the other hand, for the job offers which specifically requested a cover letter, it could be sent together with other attachments. This experiment was ranked very high in the PIE model, since the implementation was very easy. Versions A and B are displayed in figure 4.3. Similarly to the first experiment, we ran the experiment for one week and for all traffic. This experiment was again implemented in a piece of JavaScript code only.

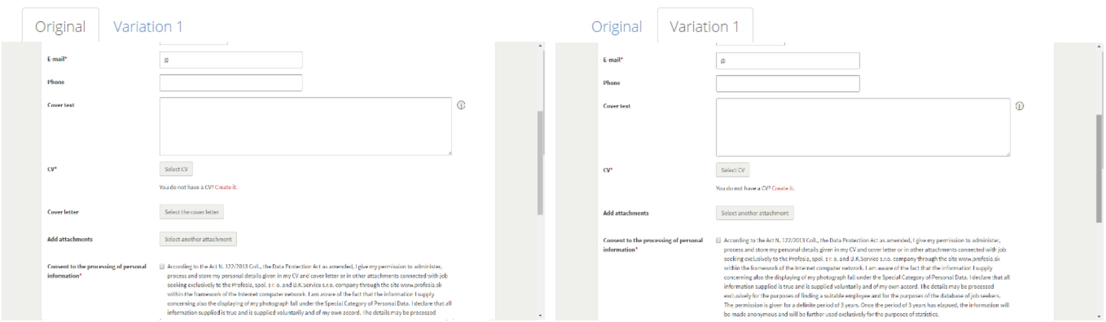

Figure 4.3: Removing the cover letter experiment

Experiment results

We believed that this experiment would be more successful than simply removing the academic degree input. Writing a cover letter is much more demanding and although it was not a required field, some users might have felt disadvantaged if they did not send the letter. However, the experiment results did not prove that version B was significantly better than version A. On the other hand, unlike the first experiment the conversion rate for version B was higher. The results can be seen in table 4.3.

Even though there was a more than 72% chance that version B was better than version A, this was not high enough for us to be convinced that implementing version B would actually be an improvement. As already mentioned in the Methodology chapter, the acceptable confidence level is usually around 95%. Nevertheless, if we believed that version B significantly improved usability, we would have also considered experiments with lower confidence levels to be successful. However, despite our assumptions, version B did not prove to be more usable than version A. Removing the upload button for the cover letter resulted in many users forgetting to upload the cover letter, even though it was specifically required in the text of the job offer. We discovered this because various companies contacted the customer support department, asking why they were suddenly receiving high percentages of applications without the cover letter. Even though the conversion rate was higher for version B, we could not consider it to be better for the users. The percentage of applications without a cover letter, even in cases where it was required, rose. That is why, in the end, the number of suitable applications was not higher. Moreover, we also needed to consider usability for the companies, which would definitely be lower if we implemented version B. Although this experiment was not successful, it showed us that simplifying the application form can indeed lead to a higher conversion rate.

4.1.4 Pre-filled input text experiment

After reviewing all the remaining input fields in the application form, we came to the conclusion that all of them are absolutely necessary. Therefore, we needed to find a different way of making filling out the form easier.

First, we compared the conversion rates of logged-in and non-logged-in users. While 60% of the logged-in users successfully finished the application form, for non-logged-in users it was only 54%. Logged-in users have the advantage that almost all the fields are already pre-filled with their information and they have all the documents needed (CV, cover letters, photo etc.) saved in their account. This is why we assumed that pre-filling input fields would increase usability and therefore lead to an increased conversion rate.

Moreover, we received information from the customer support department that many users have problems with the input called *Cover text*. The cover text is essentially the body of the email which a company receives together with all the other information and the attached documents. Next to the input field, there is also a clickable info icon which contains hints on what to put into the cover text field. Nevertheless, there were still some users who approached customer support because they were confused about what to fill in. That is why we decided to pre-fill the input value. In the input, there was the following default text:
Dear Sir/Madam,
I would like to apply for the position [position name] in your company.
I think I would be suitable for the position because of my experience/skills in... (PLEASE COMPLETE)
In case you are interested, I will gladly give you more information in person.

Table 4.4: Experiment results: Pre-filled input text

	Unique Visitors	Conversions	CR	CR difference	Chance of being better
Vs A	13816	7922	57.3%		
Vs B	13767	7959	57.8%	0.83%	78.6%

Table 4.5: Experiment results for logged-in users: Pre-filled input text

	Unique Visitors	Conversions	CR	CR difference	Chance of being better
Vs A	7027	4216	60.0%		
Vs B	6885	4120	59.8%	-0.26%	42.6%

Best regards,
[full name]
We ran the experiment on all the devices for one week and we only tested users using the Slovak version of the website. The new text was added through Google Tag Manager. The difference between the versions can be seen in figure 4.4.

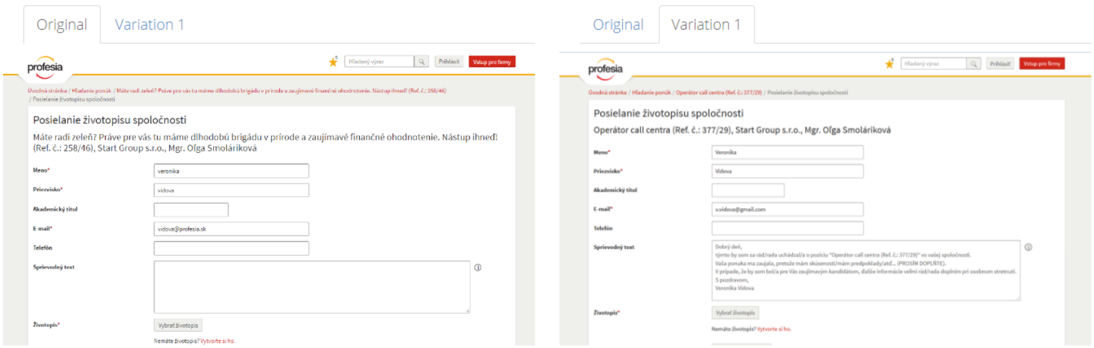

Figure 4.4: Pre-filled input text experiment

Experiment results

During the experiment, there were more conversions in version B compared to version A. However, version B did not prove to be statistically significantly better, if we take into consideration the overall results. As can be seen in table 4.4, there is a 78.6% chance that version B is better than version A. We did not consider this chance to be high enough. However, we decided to analyze the results of this experiment in more detail.

We decided to break down the results of this experiment for logged-in and non-logged-in users. The results were quite surprising. For logged-in users, the conversion rate for version B was lower than for version A 4.5. There is even a higher chance that version A is better for logged-in users.

Table 4.6: Experiment results for non-logged-in users: Pre-filled input text

	Unique Visitors	Conversions	CR	CR difference	Chance of being better
Vs A	7462	4029	54.0%		
Vs B	7499	4156	55.4%	2.64%	96.0%

On the other hand, for non-logged-in users, the conversion rate for version B is significantly higher than for version A 4.6. The chance of version B outperforming version A is almost 100%.

Since the cover text field was not a required field, we examined how many applicants had filled it in. Of the applications sent in 2016, only 47.39% had something written in the field. That means the majority of users did not feel the need to fill in the cover text field. Most logged-in users are used to the fact that all the fields are already pre-filled and they only need to accept the terms and conditions and click the send button. By pre-filling the cover text, we made the form more laborious for them, since they needed to either modify or delete the text. Non-logged-in users, on the other hand, are used to filling in all the fields themselves and therefore were pleased by having one of them already pre-filled. We also received some negative feedback from the companies. There were many users which did not change the pre-filled text at all. Since logged-in users with pre-filled inputs already had a higher conversion rate than users without pre-filled inputs, we assumed that pre-filling the cover text input would increase the conversion rate. However, since the cover text was not a required field, pre-filling it did not bring the desired results and we decided not to implement version B.

4.1.5 Green check marks experiment

Next, we decided to test hypothesis H3: "If we award users with positive feedback, more people will finish the application form because they will be notified that they are proceeding well." To encourage users to finish the form, we created a simple validation for every input field. Once the field was filled in correctly, a green check mark would appear next to it. We only created a simple validation for the text and number input fields. For the email, we used a more advanced validation. We also needed to take into consideration that logged-in users have some information pre-filled and therefore some check marks appear for them by default. We ran this experiment on traffic from all devices and for all language versions. However, we could only count users who had actually seen the green check marks. Therefore, we only took into consideration those users who had some values pre-filled or who actually started filling in the form. Since the sample size was lower, we ran the experiment for two weeks. The icons were designed by the UX designer and the functionality was developed through JavaScript. The difference between version A and version B can be seen in figure 4.5.

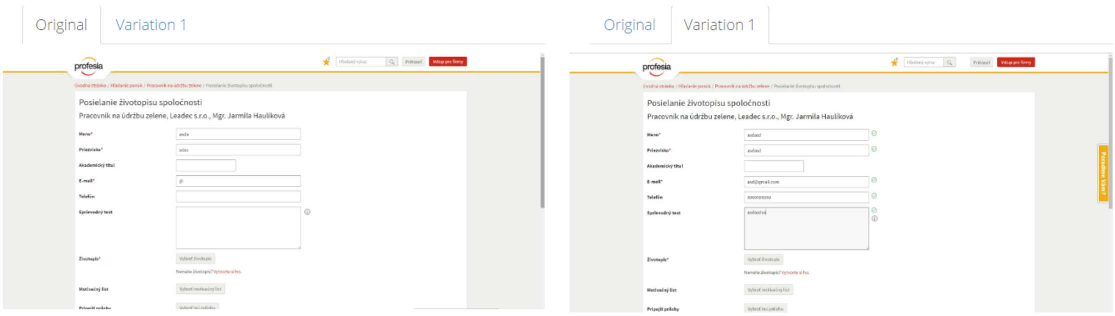

Figure 4.5: Green check marks experiment

Table 4.7: Experiment results: Green check marks

	Unique Visitors	Conversions	CR	CR difference	Chance of being better
Vs A	23016	19762	85.9%		
Vs B	22890	19601	85.6%	-0.27%	24.1%

Experiment results

The results of the experiment were disappointing, since there was almost no change in the conversion rate for version B. Before conducting more experiments on form validation, we researched similar experiments to find out why the experiment was not successful. In a study by Wroblewski [61], the conversion rates of two forms were compared. The first form was validated after hitting the submit button. The other one used inline validation similar to the type used in this experiment. The version with inline validation had a 22% higher conversion rate. That is why we expected this experiment to raise both the conversion rate and usability. However, Wroblewski also writes that not all forms are suitable for inline validation. He conducted an experiment where inline validation was used for a form with obvious answers (first name, last name, gender etc.). Based on the eye-tracking gaze path, only 30-50% of people noticed the validation message. In fact, except for the e-mail field there is no field in the application form which would require validation. Therefore, the users do not need the validation and they might even not notice it. We assume that this was exactly the case in our experiment. In the table 4.7, it can be seen that the conversion rate was higher compared to the other experiments which we ran. That was caused by the fact that for this experiment, we only counted those users who actually started filling in the form or had at least one input field pre-filled. Not only was the conversion rate for version B lower, there was over a 75% chance that the default version was better. That was probably caused by the fact that the users were confused by the check marks since they are not used to them anywhere else on the website. However, the main reason for the failure of this experiment was probably the fact that the green check marks did not improve the usability. Therefore, the conversion rate also did not rise.

Table 4.8: Experiment results: Return to the application form after creating a CV

	Unique Visitors	Conversions	CR	CR difference	Chance of being better
Vs A	3045	2227	73.1%		
Vs B	3167	2518	79.5%	8.71%	100%

4.1.6 Return to the application form after creating a CV

On Profesia.sk, it is possible to create a CV. In the application form, there is the following text: *Don't have a CV? Create one!.* The part *Create it* is a link to the page for making a CV. The 'creating a CV' page is a form consisting of seven steps. After this form is completed, the user is shown a preview of their CV. However, if the user left the application form to create the CV, after they are done creating it, they should be redirected back to the application form to finish the application. Otherwise, they have to find the job offer again. Considering that there are usually over 15,000 job offers on Profesia.sk it might be extremely difficult to find the job offer again. Therefore, we assumed that redirecting the user after creating their CV back to the application form would raise both usability and the conversion rate. We needed to run this experiment for two weeks since the sample size was reduced only to those users who left the application form to create a CV. That was approximately 1.5% of all the users who entered the application form. One half of users were redirected back to the application form and the other half to the preview of the CV. This experiment was developed by the backend developer since it was not possible to implement the redirect in the frontend only.

Experiment results

The redirect back to the application form after having finished creating the CV proved to be a logical step. Although we were confident that this adjustment would improve usability, we were doubtful about the increased conversion rate. In our experiments, we count the conversions per user. This means that if a user sees version A or B, they might not send the application immediately. If they return before their cookie expires and send the application, we still count them as a user who converted. Therefore, we expected that even if the user was not redirected back to the application form, they would still want to send the application and despite the difficulties, they would find the job offer again and finish the application form. However, the results of the experiment proved that finding the job offer again was causing many users problems and they did not return to the application form to finish their application. As can be seen in table 4.8, in version B 8.71% more users converted compared to version A which is a significant improvement. That is why we consider this experiment to be particularly successful in improving both usability and the conversion rate.

4.1.7 Not required CV for mobile users

Firstly, we ran multiple small experiments which were ranked high in the PIE model because of the ease of implementation. However, after implementing all kinds of small changes we were still not getting enough positive results. Therefore, we decided to analyze the reason why users leave the page. We chose to do that by creating a poll using the Hotjar tool. Just before leaving the application form without submitting it, the poll appeared on the page asking: *Why have you decided not to send the application?* The possible answers were:

- **A:** I don't have the required documents.
- **B:** I need some time to think about it.
- **C:** I got to this page accidentally.
- **D:** I was surprised by the high number of required information.
- **E:** Other

After a user chose one of the options, they could also leave an additional text answer. We collected responses from 229 users. The results of the poll are shown in figure 4.6. 32.8%

Figure 4.6: Results of the poll

of the respondents said that they did not send the application because they were missing required documents. It is difficult to raise usability or the conversion rate for these users, since they simply cannot send the application without these documents. Moreover, when we analyzed the conversion rate for mobile users, we found a great difference between

Table 4.9: Experiment results for logged in users: Not required CV for mobile users

	Unique Visitors	Conversions	CR	CR difference	Chance of being better
Vs A	5129	2770	54.0%		
Vs B	5202	2893	55.6%	2.97%	95.1%

Table 4.10: Experiment results for non-logged-in users: Not required CV for mobile users

	Unique Visitors	Conversions	CR	CR difference	Chance of being better
Vs A	4213	1341	31.8%		
Vs B	4119	1455	35.3%	11.0%	100%

Table 4.11: Experiment results for all users: Not required CV for mobile users

	Unique Visitors	Conversions	CR	CR difference	Chance of being better
Vs A	9342	4111	44.0%		
Vs B	9321	4348	46.6%	6.0%	100%

logged-in and non-logged-in users. While logged-in mobile users had a conversion rate of 54%, for non-logged-in mobile users it was only 32%. We assumed that the reason for such a low conversion rate is that users do not have the CV saved on their phone. They only browse through the job offers on their phone and then send the application from their desktop computer. Since logged-in users can save their CV and other documents in their account, it is much easier for them to send the application even from a mobile device. Furthermore, we analyzed which kinds of job offers had the worst conversion rate. We found that for job offers for lower-level positions, the conversion rate of the application form was much worse. We believed that for the majority of these job offers, it was not necessary for companies to require a CV. That is why we decided that uploading a CV will be an optional field in the application form for mobile users. We expected that this would considerably raise the conversion rate for mobile users which are not logged in. Since there would be no attachment required they would be able to easily finish the application form without having to use their desktop computer. Due to the fact that the sample size was reduced to only mobile and tablet traffic, we needed to run the experiment for at least two weeks. For implementing this experiment it was sufficient to modify the form using JavaScript.

Experiment results

As we expected, version B with an optional CV had a significantly higher conversion rate than version A. The results broken down into logged-in and non-logged-in users can be seen in tables 4.9 4.10 The overall results of the experiment are stated in table 4.11. The most significant uplift, 11.0%, was detected with non-logged-in users. However, for logged in users as well, the difference between the conversion rates was so high that we can say with 95.1% certainty that version B is better than version A. Moreover, in the

Table 4.12: Experiment results for all users: Warning the user before leaving

	Unique Visitors	Conversions	CR	CR difference	Chance of being better
Vs A	16250	9652	59.4%		
Vs B	16089	9408	58.5%	-1.55%	4.59%

overall results, the uplift in the conversion rate was 6%. This proved that increasing the usability of the application form by lowering the requirements leads to a rapid increase in the conversion rate. However, we also needed to consider usability for companies. We received many complaints that companies were receiving applications without a CV even for job offers where the CV was desired. Even though the conversion rate rose, many of the applications were useless since the company was not interested in an application without a CV. That is why we decided to leave the CV as a required field. Nevertheless, we are planning on implementing a new functionality where the companies can set whether the CV should be required or not for each job offer. The company can decide themselves if they would like to receive more job applications without a CV or if the CV is absolutely necessary for them. This way, the usability for both the companies and the users will be increased. Moreover, based on this experiment we can also say that this change will lead to a higher conversion rate. Although, we decided not to implement version B, we still consider this experiment to be successful.

4.1.8 Warning the user before leaving

In the next experiment, we tried to reverse our thinking process. We wanted to raise the conversion rate without regard for usability. Since our main goal is for the users to finish the application form, most other actions which users do on the application form page are undesirable. That is why we decided to display a message before a user leaves the application form page saying: ***Don't miss your chance*** *This job offer ends in X days. Don't miss your chance and send the application now. In case you don't have all the required documents, bookmark the job offer and send the application later.* The screenshot of version B can be seen in figure 4.7. This message was displayed before the user left the application form page, except for the cases when they left to register, sign in or create a CV. We ran this experiment for one week on all devices and for all language versions. The experiment was implemented through a JavaScript code inserted via Google Tag Manager.

Experiment results

Although this experiment was not aimed at improving usability, we expected the conversion rate to rise. However, this experiment was not successful. Moreover, in version B, there were fewer conversions.

As can be seen in table 4.12, there is a more than 1.5% decrease in the conversion rate between version B and version A. We expected that creating time pressure on the users

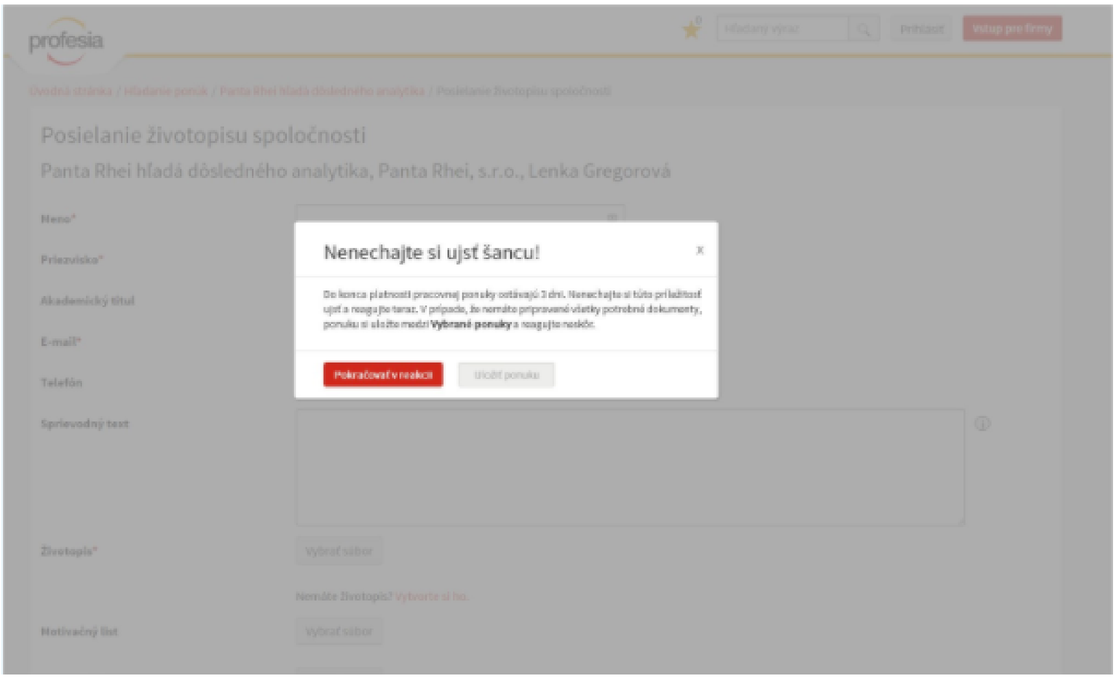

Figure 4.7: Warning the user before leaving experiment

by reminding them when the job offer ends would persuade them to send the application immediately. Although we were aware that displaying the message could be annoying for the users and therefore actually decrease usability, our only goal in this experiment was to raise the conversion rate. However, the results suggest that decreasing usability leads to a lower conversion rate. Naturally, we decided not to implement version B and to focus on increasing usability in the next experiments.

4.1.9 Shortening the terms and conditions

Apart from the previously mentioned experiments, we also decided to run a few tests for improving the visual fluency. In order to eliminate potential distractions, we decided to shorten the terms and conditions at the bottom of the application form. We ran two experiments for this hypothesis. In the first one, we reduced the height of the terms and conditions and we made the text scrollable. In the second test, we displayed only the first three lines of the terms and the rest could be seen after the text *See full text* was clicked. Although this is not a usability improvement as such, these experiments focused more on enhancing the whole user experience. Moreover, they were ranked very high for ease of implementation. We ran both of these experiments for one week and on all devices. Both versions of the shorter terms and conditions were designed by the user experience designer and were developed by the frontend developer.

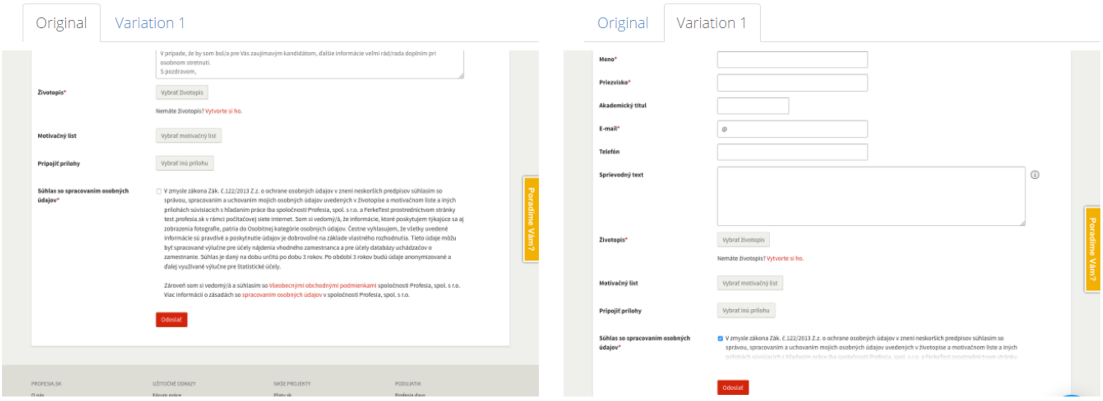

Figure 4.8: Terms and conditions experiment no.1

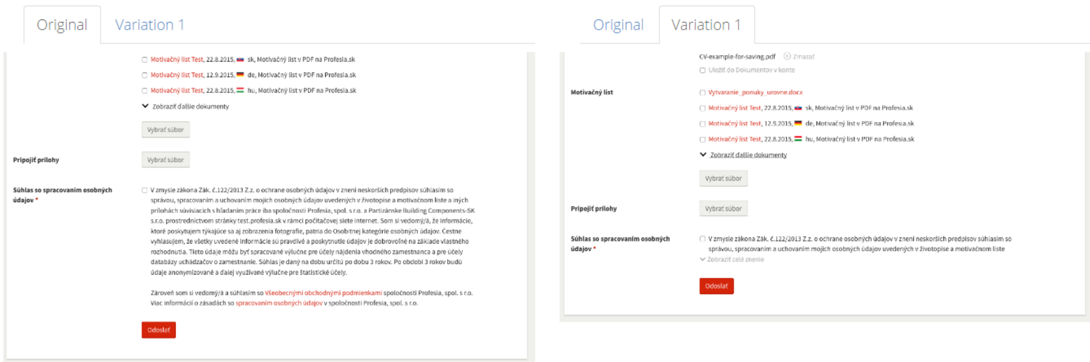

Figure 4.9: Terms and conditions experiment no.2

Table 4.13: Experiment results for all users: Terms and conditions experiment no.1

	Unique Visitors	Conversions	CR	CR difference	Chance of being better
Vs A	14981	8932	59.6%		
Vs B	15033	9011	59.9%	0.535%	71.1%

Experiment results

The results of the first experiment 4.8, in which the terms and conditions were scrollable, are displayed in table 4.13. Although version B had a higher conversion rate, we could not be confident enough that the version is actually better than version A. The difference in conversion rates for the second version of the experiment, in which the terms and conditions were displayed on click, was even smaller. Neither of these experiments proved to have an impact on either the conversion rate or the usability of the website. We assume that the majority of users do not read the terms and conditions and therefore are not affected by the form in which they are displayed. That is why we decided to keep the default version of the website.

Table 4.14: Experiment results for all users: Terms and conditions experiment No.2

	Unique Visitors	Conversions	CR	CR difference	Chance of being better
Vs A	15040	8675	57.7%		
Vs B	15011	8651	57.6%	-0.084%	46.8%

4.2 Experiments done on other pages

Apart from doing experiments on the application form page, we ran a number of other experiments on other subpages. If we discovered a usability issue or room for usability improvement, we proposed possible solutions, ranked them and ran an experiment for the solution with the highest ranking. Most of these experiments were aimed at increasing the number of applications sent. The first three experiments described in this section were again focused on the job applicants. The last experiment shows how increasing usability for companies led to a higher number of purchases.

4.2.1 New button in the offer detail

As previously mentioned, on the job offer detail page there is an 82% drop off. That means that 82% of the users who see the detail of a job offer do not continue onto the application form page. Although this number is influenced by several factors which are out of the hands of Profesia.sk, we decided that we would try to increase the number of entrances to the application form. Our assumption was that the button for entering the application form was not visible enough. On the job detail page, there are two buttons through which it is possible to enter the application form page. One is at the bottom of the page which is below the fold and therefore less visible. The other one is in the sidebar menu. According to Nielsen [62], a user never looks at anything that looks like an advertisement. Therefore, he advises not to put important content in the right-hand column. Based on this article, we assumed that the application form button in the right sidebar was not visible enough. That is why we decided to create a Hotjar heatmap on the job offer detail page which can be seen in figure 4.10 *Send a CV to the company* is the first option in the sidebar, but from the heatmap it is clear that it is overseen by the majority of users. Most of the users use the call-to-action button on the bottom of the page. We also confirmed this by checking the statistics in Google Analytics. From all the pageviews of the application form, 95% of them entered from the call-to-action button, only 3% from the right sidebar and 2% entered from other sources. That is why we decided to emphasize the link to the application form below the fold. Moreover, we wanted to motivate users to send the application by the following text: *Sending the application will not take longer than 3 minutes.* By informing them of the simplicity of the form, we wanted to encourage them to enter the application form. Moreover, we expected that the usability would be improved since the users would not need to look for the button to the application form but it would be immediately visible. Naturally, the main goal of this experiment was to raise the number of applications sent and not the number of entrances to the application form. The difference between versions can be

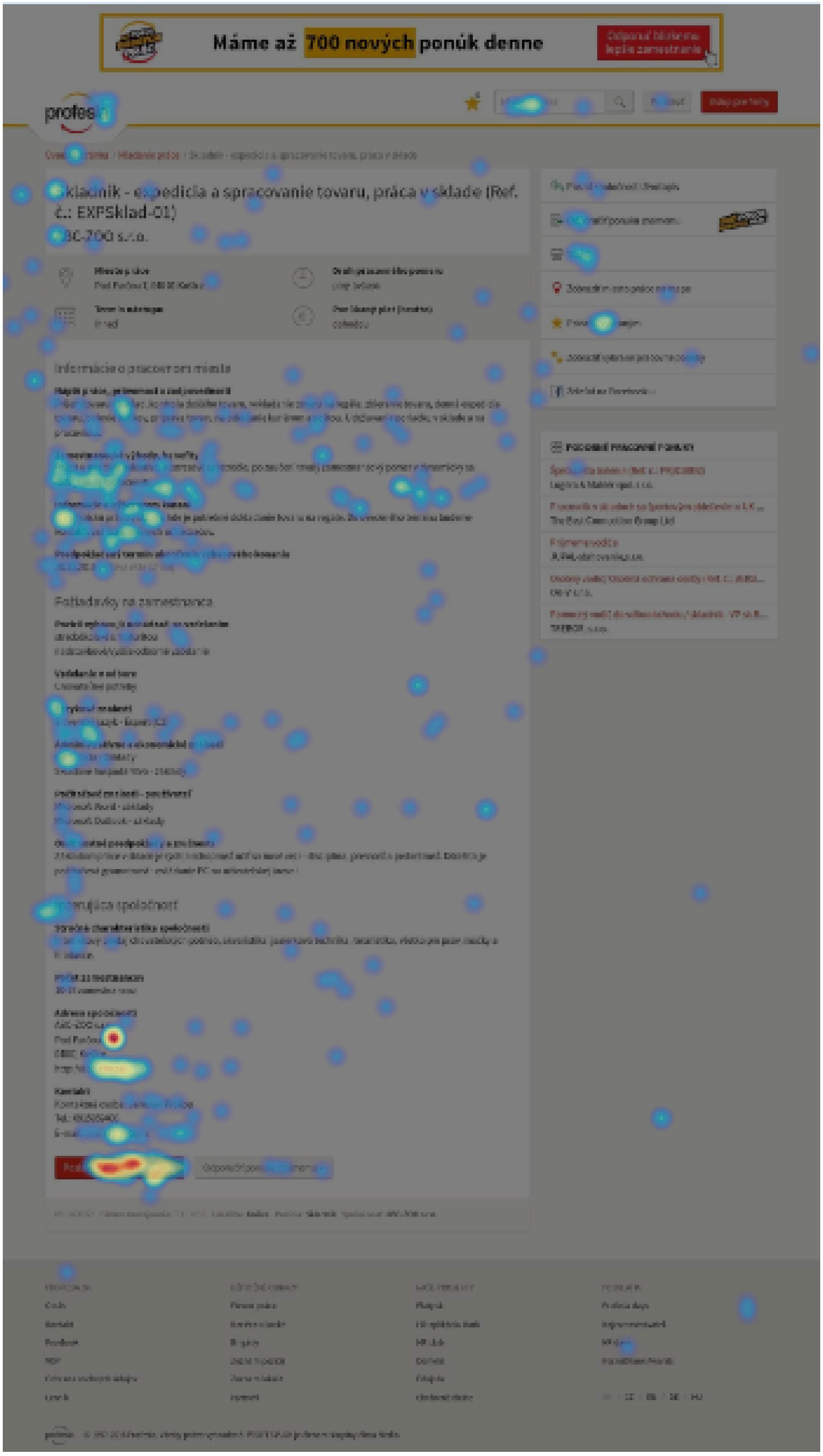

Figure 4.10: Heatmap of the job offer detail page

Table 4.15: Experiment results: New button in the offer detail experiment

	Unique Visitors	Conversions	CR	CR difference	Chance of being better
Vs A	168431	8104	4.81%		
Vs B	169010	8197	4.85%	0.801%	70.0%

seen in figure 4.11. We ran this experiment for one week on the Slovak version of the website only. The modifications in version B were implemented using JavaScript.

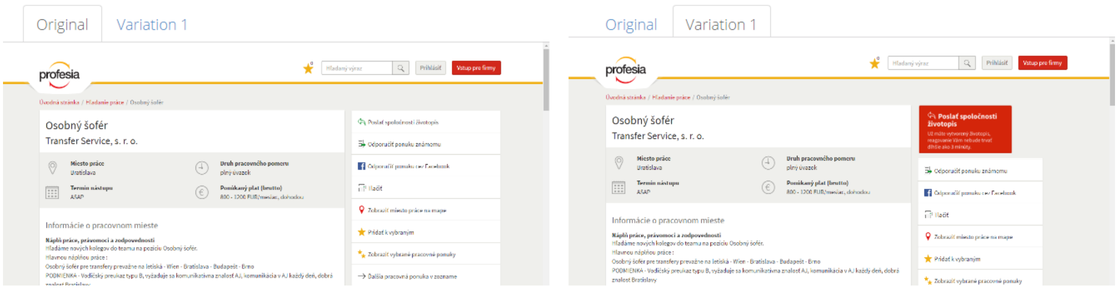

Figure 4.11: New button in the offer detail

Experiment results

As expected, the red button attracted more attention than the button in the right sidebar. While only 3% of all the users entering the application form entered through the sidebar, for the red button it was 9,7%. However, the majority of users are used to using the red button at the bottom of the job offer, after they have read the whole text. Since the goal of this experiment was to raise the number of job applications sent, we compared the conversion rates of version A and version B. As can be seen in table 4.15, the number of users per version is much higher compared to the experiments which we did on the application form page. That is why during the one week experiment even when the difference in the conversion rates is not so high, the results should be statistically relevant. Nevertheless, the conversion rates for the two versions were not too different.

The chance of version B being better is only 70%. In this experiment, we combined two assumptions. Firstly, we wanted to highlight the possibility of entering the application form and, secondly, we wanted to use a motivational text to inform users about the ease of filling out the application form. The experiment showed that finding the entrance to the application form was not a problem for the users since the number of entrances to the application form was about the same for both versions. The slight improvement in the conversion rate could be caused by the motivational text which was used in the button. Although the results of the experiment were not convincing enough, we will consider using other methods of informing the users of the ease of filling out the form.

Table 4.16: Experiment results: New button in the list of bookmarked offers

	Unique Visitors	Conversions	CR	CR difference	Chance of being better
Vs A	3301	1480	44.8%		
Vs B	3397	1592	46.9%	4.53%	95.3%

4.2.2 New button in the list of bookmarked offers

For users who are logged in, it is possible to bookmark a job offer. They can then find the list of bookmarked offers in their account. It is also possible to add a note to the bookmarked offer. By bookmarking the offer, the user shows a particular interest in it and is therefore likely to send an application for it. These users are logged in and are using more *advanced* features of the website. That is why we assumed that their engagement is relatively high and therefore they should be more likely to be affected by the changes made on the website. We decided to create a direct link from the list of bookmarked offers to the application form. As can be seen in figure 4.12, the only action on the list of bookmarked offers was the link to the job offer detail and removing the job offer from the list. For version B we added the option to *Send a CV to the company*. The link led directly to the application form. By adding this option, we wanted to save the user one step towards sending the application and therefore to increase the usability of the website. The sample size consisted of users who were logged in and had at least one job offer bookmarked. The new button was added through Google Tag Manager.

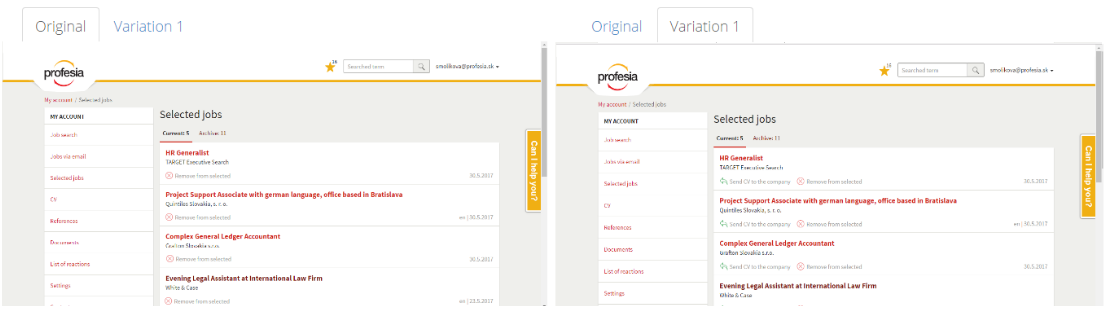

Figure 4.12: New button in the list of bookmarked offers

Experiment results

As the results of the experiment showed, most users wanted to check the job offer detail again, before sending the application form. Nevertheless, the conversion rate for version B was higher than for version A. In version A, 62.1% of users who entered the list of bookmarked job offers continued on to a job detail. The conversion rate in both versions represent the number of users who entered the list of bookmarked job offers and then sent an application. As can be seen in table 4.16, there is an over 95% chance that version B is better than version A. It is interesting that although the conversion rate for version B was higher, the number of users who clicked on the newly added option, *Send a CV to the company*, was not so high. Out of 3397 users only 254 actually used the new link, which is a click-through rate of only 7.48%. Nevertheless, the click-through rate to job offer detail, compared to version A, was a bit higher. While in version A 62.1% of the users clicked on the name of the job offer to enter the offer detail, in version B it was 63%. That indicates that although the number of users who clicked on *Send a CV to the company* was not so high, the fact that the option was displayed there influenced them positively to send the application. Moreover, the results of this experiment led us to an assumption that experiments run on users who are more engaged with the website can yield better results. However, we needed to confirm this hypothesis by running more experiments. We evaluated this experiment as a success and implemented version B for all traffic.

4.2.3 Highlighting an ending offer in the list of bookmarked offers

Since the previous experiment with a new button in the list of bookmarked offers was successful, we wanted to run more experiments on this page. When rating the site using Net Promoter Score, users are encouraged to leave some textual feedback as well. Through regular checking of these answers, we came across following feedback: *I bookmarked an offer and when I later checked the list of bookmarked offers, it was no longer there. Then I found out that the offer had already ended.* By bookmarking an offer, the user shows interest in the position. They should be notified when the offer is about to end so that they can reconsider whether they want to send an application. Therefore, we decided to add a label to the list of bookmarked offers which was displayed with the offers ending in the next three days. The following text was written next to the name of the offers: *This offer expires soon!*. A bookmarked offer with the label is displayed in figure 4.13 However,

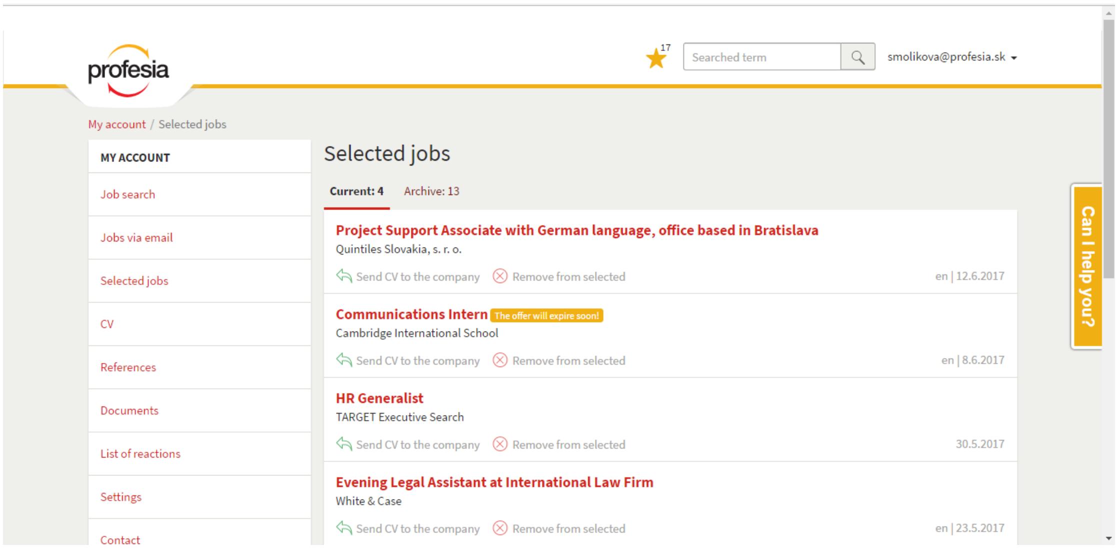

Figure 4.13: Highlighting an ending offer in the list of bookmarked offers

Table 4.17: Experiment results: Highlighting an ending offer in the list of bookmarked offers

	Offers displayed	Conversions	CR	CR difference
Without button	5380	2528	47.0%	
With button	6733	3501	52.0%	10.6%

for this experiment we needed to change the evaluation metrics. Since the label is shown only for ending offers, we could not simply divide the traffic and measure the conversion rate. We did not want to compare the overall conversion rate but rather the conversion rate of offers with the label with the ones without it. Therefore, we decided to show version B for all traffic and after one week compare the conversion rate of offers which had the label with the ones which did not. We measured when the label was displayed and clicked on through Google Analytics *events*. This experiment required information about the ending date of an offer. Therefore, it was developed by the backend developer.

Experiment results

In this experiment we wanted to evaluate if time pressure actually motivates users to convert and send the application. From the results displayed in table 4.17, it can be seen that the conversion rate for offers with the label is indeed higher. Based on the data gathered throughout this one week, we decided to leave the label in the list of bookmarked offers. Moreover, we decided to add a similar label to the job offer listing as well. We measured the performance of the label in the job offer listings through a custom dimension in the Google Analytics *Enhanced ecommerce* plug-in. The click-through rate for the job offers with this label was 26% higher than the overall click-through rate. With this experiment we not only increased the conversion rate, but we also increased usability which was proven by the fact that after introducing the label on the job offer listing, the Net Promoter Score increased from 43.88 to 46.73.

4.2.4 Warning companies before filling out the offer form

The last experiment which we describe in this thesis is the only one which was not aimed at raising the number of applications sent. This experiment was designed to deal with a specific usability issue in the form for creating a job offer. There are two ways that a company can pay for a job offer. The simplest option is to pay for a single offer to be published for a specific period of time. If the company uses Profesia.sk often and they are publishing multiple job offers, it is cheaper for them to buy a credit package. When they publish an offer, the credit is automatically subtracted from their account. The credit package is quite popular and more than half of all of the offers are published using credits. If the company is out of credits, they are reminded to buy more credits. Nevertheless, we received a number of complaints about the placement of the note on the excerpt credit. When the company wants to add a new job offer, the first step is to fill out all the necessary information. Since there is a lot of information required, creating a new job offer can take an extensive amount of time. Afterwards, they are asked how long the offer should be published for as well as the payment details. If the company has bought a credit package before and they have run out of credits, they will be shown the following message: *You have run out of credits. Buy new ones.*, which is also a link to an order form. However, if the company clicks on this link, all the information about the new job offer, which they previously filled in, is lost. We have received complaints not only during regular user testing, but also through our customer support service. This was obviously an enormous usability problem. That is why we decided to check the credit status at the very beginning of the form for adding a job offer. When the form was opened and if the company had run out of credits, a modal window was shown with the following text: ***Advertise with discount*** *You have run out of credits. If you buy a credit package, you can save from 25 to 50% compared to the price of a single offer. The package also includes access to our database of CVs.* The visualization of version B can be seen in figure 4.14. We wanted to compare the number of bought credit packages and single offers for both versions. However, the main problem with this experiment was the sample size. We could only count companies which entered the new job offer form and had run out of credits. That is approximately 50 companies per week. The conversion rate for the default version of the website for the credit package was around 72%. That means that if the company was shown the message about running out of credits, 72% of them clicked on the link and bought more credits. 15% of users continued and bought a single offer. The remaining 3% of users did not end up buying either a credit package or a single offer. According to the sample size calculator [4], if we ran the experiment for 4 weeks, the improvement in the conversion rate for a credit package needed to be more than 15%, so that we could say with at least 95% certainty that the outcome of the experiment is not the result of a coincidence. Moreover, since for the single packages the default conversion rate was around 12%, the difference between the versions after four weeks should be at least 67%. As it was already mentioned, it is not advisable to run the experiment for a period longer than 4 weeks due to possible sample pollution. That is why we decided to run this experiment for the longest period possible. The implementation required changes in the backend code and therefore it was done by the backend developer.

Experiment results

The goal of this experiment was to

1. Increase the number of users who bought a credit package

2. Decrease the number of users who made no purchase

For the first goal, we managed to prove that version B is better. As can be seen in table 4.18, even though the sample size was not too high, the difference in conversion

[4] https://abtestguide.com/abtestsize/

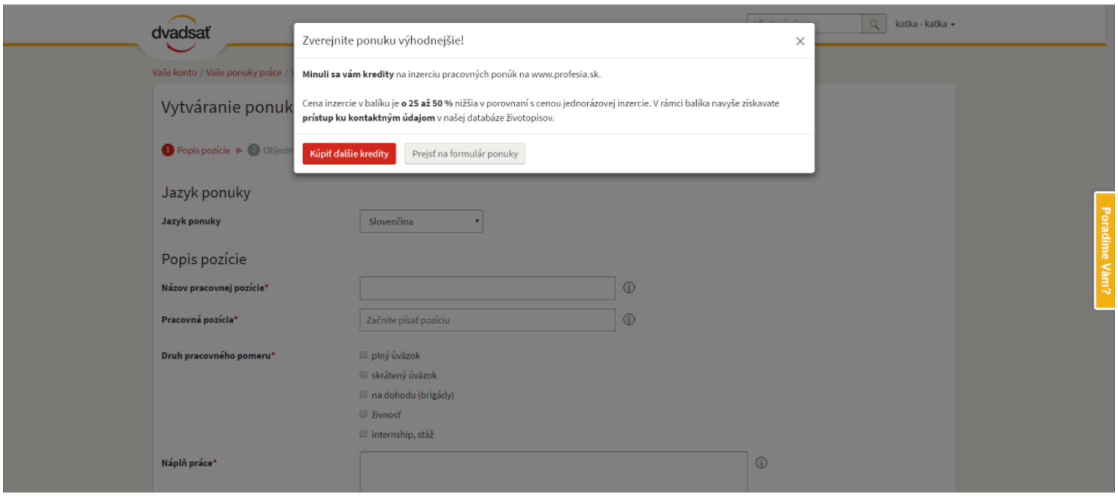

Figure 4.14: Warning companies before filling out the offer form

Table 4.18: Experiment results: Warning companies before filling out the offer form - Conversion for the credit package

	Unique Visitors	Conversions	CR	CR difference	Chance of being better
Vs A	107	77	72.0%		
Vs B	111	94	84.7%	17.7%	98.8%

Table 4.19: Experiment results: Warning companies before filling out the offer form - Overall conversion

	Unique Visitors	Conversions	CR	CR difference	Chance of being better
Vs A	107	103	96.3%		
Vs B	111	108	97.3%	1.08%	65.8%

rates between both versions was sufficient for us to tell that version B is better with a 98.8% confidence. For the evaluation of the second goal we first needed to reverse the formulation of the goal, since the A/B testing Bayesian calculator is suitable only for detecting positive and not negative effect. We changed the goal formulation from *Decrease the number of users who made no purchase* to *Increase the number of users who made some purchase*. The results for this goal can be seen in table 4.19. In the table, the users who converted are the ones who bought either a credit package or a single offer. Although the difference between the two versions is not significant enough, there was some increase in the conversion rate for version B. Even though there was not a significantly higher number of overall purchases in version B, we still evaluate this experiment as a success. The main goal of this experiment was to get more users to buy a credit package instead of a single offer. Therefore, we decided to implement version B for all traffic. It was also confirmed that usability for companies was increased, since the

Net Promoter Score for companies slightly increased from 36.04 to 38.61.

CHAPTER 5

Discussion

In this chapter, we will elaborate on the results of the experiments. We will define our thoughts on why some kinds of experiments were more successful than others. Last but not least, based on the result of the experiments, we will answer the main research question of this thesis: Does increased usability lead to an increased conversion rate?

In the previous chapter, 14 experiments were presented together. Although not all of them were successful, they all helped us to understand our users better and propose better solutions in the future. That is proven by the fact that the more experiments we developed, the more positive results we got. We also conducted many small experiments which are not described in this thesis. We also did not specify all the proposed solutions but we only described the solutions which we tested. The results of all the experiments are summed up in table 5.1. We assigned each experiment a number from 1 to 10, representing the degree of increased usability. Since usability is extremely difficult to measure, this number is highly subjective. It only represents our assessment based on the Net Promoter Score, feedback from the customer support, and our own impression of the experiment.

5.1 Experiments done on the application form page

As can be seen in table 5.1, out of the 10 experiments conducted on the application form page, only three were successful. This was probably due to the fact that a high percentage of users who leave the application form do not have a CV, which is a required field, and cannot continue. Therefore, even by making all kinds of adjustments to the application form, we cannot influence these cases. An analogy to this case could be an e-shop. If users want to buy something, they need a credit card. If they do not have it, the usability of the website can be perfect, but they will not be able to buy anything. The only possible way to increase the usability for these users would be to create an alternative payment option. In the experiment *Optional CV for mobile users*, we proved

Table 5.1: Experiment results summary

Name of experiment	Increase in usability	CR difference	Successful	Implemented later
Experiments done on the application form page				
Modifying captions of the upload buttons	5	3.66%	yes	yes
Removing the academic degree input	2	-0.39%	no	no
Removing the cover letter	3	0.58%	no	no
Pre-filled input text experiment	5	0.83%	no	no
Green check marks experiment	2	-0.27%	no	no
Return to the application form after creating a CV	9	8.71%	yes	yes
Optional CV for mobile users	6	6.0%	yes	no
Warning the user before leaving	1	-1.55%	no	no
Shorter terms and conditions no.1	2	0.54%	no	no
Shorter terms and conditions no.2	2	-0.08%	no	no
Experiments done on other pages				
New button in the offer detail	4	0.80%	no	no
New button in the list of bookmarked offers	6	4.53%	yes	yes
Highlighting an ending offer in the list of bookmarked offers	7	10.6%	yes	yes
Warning companies before filling out the offer form	10	17.7%	yes	yes

that not requiring a CV notably increases the conversion rate. That is why in the future, we plan on creating the option for companies to choose whether they require a CV. Based on the experiment, we can already prove to them that if they do not demand a CV they will receive more applications. This will be especially useful for low-level positions such as construction workers or factory workers.

In table 5.1, we can also see that all the experiments on the application form page which were successful had an increased usability ranking of 5 or higher. The experiment which we ranked as the highest usability improvement *Return to the application form after creating a CV* also achieved a significant difference in the conversion rate of 8.71%. In this experiment, we actually fixed a significant usability issue. Experiments such as *Green check marks experiment* or *Removing the academic degree input* were aimed more at encouraging users to continue and to simplify the process of completing the form. They did not actually attempt to fix a particular usability problem.

The results of the *Warning the user before leaving* experiment are also fairly interesting. We conducted this experiment without any regard to usability. What is more, we were aware that this adjustment would actually harm usability. The goal of this experiment was to increase the conversion rate at all costs. However, this experiment proved that decreasing usability also leads to a decreased conversion rate.

To sum up, from the pre-analysis, we gained the impression that the application form page has a high potential. 42% drop-off from a simple application form seemed very high and therefore we believed that there was great room for improvement. Not redirecting users back to the application form after they have finished creating their CV was an obvious usability issue. Fixing it led to a significant increase in the conversion rate. However, the main usability issue which users are facing is the required CV. In the *Optional CV for mobile users* experiment, we proved that if we tackle this issue, the conversion rate will rise. The other experiments run on the application form page did not have a very significant impact on usability. Subsequently, the conversion rate was also not significantly different.

5.2 Experiments done on other pages

On the other hand, the experiments done on other pages yielded better results. Except for the *New button in the offer detail* experiment, all the experiments were successful. Modifying the list of bookmarked offers led to increased conversion rates in both cases. We assumed that the increased conversions were also caused by the fact that the sample size consisted only of logged-in users. Therefore, we presumed that users who are more engaged with the website are easier to influence. However, when we implemented the highlighting of ending offers to job offer listings, where the majority of users are not logged in, the difference in the conversion rate was even higher. This proved that improving the usability leads to an increased conversion rate regardless of the type of user.

The *Warning companies before filling out the offer form* experiment was aimed at fixing a major usability problem. Companies were repeatedly complaining about losing all the filled in information after buying a credit package. By simply reminding them to buy the package before they fill out the order, we increased the number of bought credit packages by 17.7% compared to version A. Not only did we fix the usability issue, we also increased the revenue. This experiment was the most successful out of all the experiments which we conducted. Although we only had a limited sample size of around 100 users, the 17.7% increase in conversion rate was high enough for the results to be statistically significant.

We consider the experiments done on pages other than the application form page to be quite successful. Three out of four experiments achieved a considerably higher conversion rate for version B.

5.3 Effect of usability on the conversion rate

In conclusion, even though the results of the experiments were miscellaneous, there is a clear relationship between the degree to which the experiment improved usability and the growth of the conversion rate. The experiments which did not result in a significant difference in the conversion rates were usually aimed at improving usability in general or enhancing the user experience. However, they had little effect on both the usability and the conversion rate. On the other hand, when the experiments were aimed at a specific usability issue reported by users, fixing the issue always led to higher conversion rates. This relationship can be seen in the scatter graph in figure 5.1.

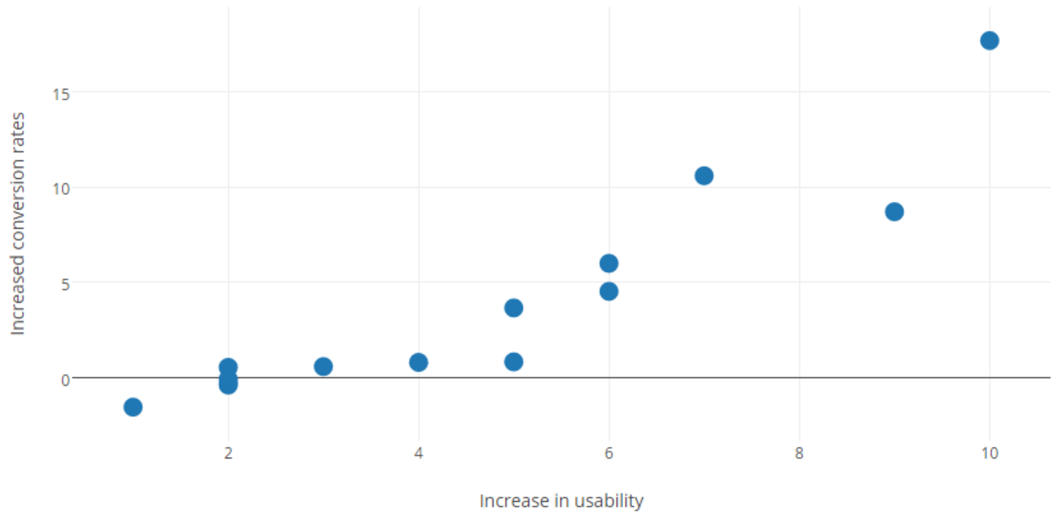

Figure 5.1: Scatter graph of the relationship between the conversion rate and usability

Although all the experiments were conducted on one job searching portal, we can assume that these results apply for most ecommerce websites. Since profesia.sk is the most used job searching portal in Slovakia, its user base contains all kinds of users. The age of users who visited Profesia.sk can be seen on the screenshot from Google Analytics in figure 5.2. Moreover, Google Analytics also provides statistics for users' interests. As can be seen in

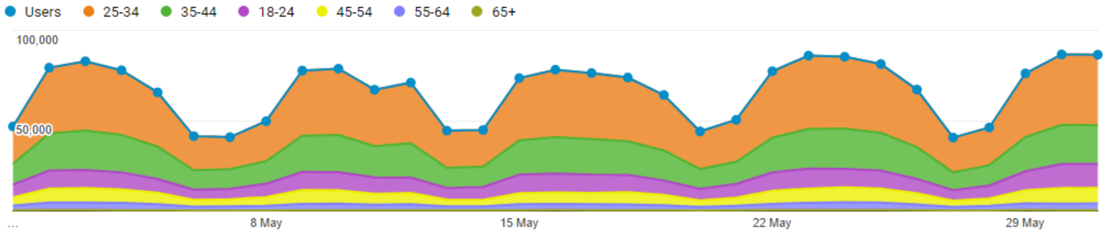

Figure 5.2: Age groups of visitors of Profesia.sk in May 2017

figure 5.3, visitors of profesia.sk are certainly not a homogeneous group. This makes the website ideal for conducting experiments, since the sample contains many different user groups. Therefore, there is a high probability that if the experiment was successful on profesia.sk, the same would apply for many other websites.

Affinity Category (reach)	Users	Sessions	Pages/Session	Avg. Session Duration	% New Sessions	Bounce Rate
	807,598 % of Total: 68.24% (1,183,429)	3,258,761 % of Total: 78.79% (4,136,178)	7.93 Avg for View: 7.93 (0.00%)	00:05:36 Avg for View: 00:05:35 (0.36%)	9.61% Avg for View: 16.07% (-40.18%)	14.74% Avg for View: 15.52% (-5.04%)
1. Outdoor Enthusiasts	608,157 (4.23%)	2,501,373 (4.40%)	7.63	00:05:19	8.42%	14.87%
2. Green Living Enthusiasts	588,431 (4.09%)	2,531,864 (4.45%)	7.97	00:05:38	7.55%	14.73%
3. Foodies	526,808 (3.66%)	2,225,930 (3.92%)	7.92	00:05:34	7.58%	14.56%
4. Movie Lovers	508,358 (3.53%)	2,074,784 (3.65%)	8.08	00:05:43	8.19%	14.17%
5. Art & Theater Aficionados	471,512 (3.28%)	1,936,396 (3.41%)	8.17	00:05:44	8.18%	14.24%
6. Sports Fans	465,332 (3.23%)	2,167,181 (3.81%)	8.28	00:05:49	6.49%	14.41%
7. News Junkies/Entertainment & Celebrity News Junkies	454,674 (3.16%)	1,917,595 (3.37%)	7.79	00:05:23	8.12%	14.32%
8. Business Professionals	420,273 (2.92%)	1,892,756 (3.33%)	8.47	00:05:57	6.93%	13.57%
9. Cooking Enthusiasts/Aspiring Chefs	408,732 (2.84%)	1,831,228 (3.22%)	7.87	00:05:28	6.53%	14.86%
10. Travel Buffs	405,890 (2.82%)	1,670,341 (2.94%)	8.08	00:05:36	7.81%	13.99%

Figure 5.3: Affinity categories of visitors of Profesia.sk in May 2017

To sum up, even though there were a high number of unsuccessful experiments, all the experiments which were aimed at a specific usability issue had a strong positive impact on the conversion rate. Moreover, an experiment which did lower usability also led to a lower conversion rate. That is why we can say that the changes in usability have a powerful effect on the conversion rate.

CHAPTER 6

Critical reflection

The question which our research tried to answer was: *Does improving usability lead to an increased conversion rate?* However, when evaluating the experiments, we came across the challenge of how to determine if usability has actually been improved. We believe that the experiments which produced negative results did not actually significantly improve usability. In this chapter, we will evaluate the correctness of the methodology and the validity of our findings. We will state possible improvements to the process. Lastly, we will compare our results with the papers dealing with similar topics.

6.1 Methodology assessment

We decided to use an iterative approach to conduct the experiments. It consisted of five stages: finding usability issues, proposing solutions, ranking the solutions, A/B testing and an evaluation of the results. Retrospectively, we believe that this methodology was suitable for our research. Nevertheless, in each stage there could be great improvements made.

Possibly the most neglected phase in our methodology was *finding usability issues.* First, we did the initial analysis of user behavior through Google Analytics. After discovering the high drop-off rate from the application form page, we assumed that there was a usability issue and ran a number of experiments trying to improve the form. However, the experiments were aimed more at improving the user experience rather than usability. First, we need to consider the difference between usability and user experience. According to the International Organization for Standardization, usability is defined as the *extent to which a system, product or service can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use.* On the other hand, they define user experience as a *person's perceptions and responses resulting from the use and/or anticipated use of a product, system or service.* [63] Some of our experiments such as the *Green check marks experiment* or the *Shortening terms* *and conditions* experiment were focused on improving users' visual perception of the website. A note for ISOs user experience definition also states: *Usability, when interpreted from the perspective of the users' personal goals, can include the kind of perceptual and emotional aspects typically associated with user experience.* [63] To conclude, it is difficult to assess if the adjustments we made actually improved usability. After conducting a user poll, described in section 4.1.7, we learned that for many users, the main issue in the application form is the CV. Therefore, one of the reasons why some of the experiments on the application form page were not successful, might be that we did not identify the usability issue correctly. Instead of focusing on the core problem of the form, we made many small adjustments that had little effect. On the other hand, the experiments which dealt with issues directly reported by the users were always successful. If we had chosen a different approach to finding the issues, for example through user testing or conducting more surveys, we might have been more successful in identifying the actual usability flaws.

Secondly, we are doubtful whether the ranking of the solutions using the PIE model was the ideal approach for our research. We rated each proposed solution for potential, importance and ease of implementation. For the application form page, the potential and importance were always the same. Therefore, we chose which experiments to conduct based only on the ease of implementation. This resulted in only developing experiments which were simple to carry out, however, they had no significant impact on the users. Had the ranking model also considered our confidence in the experiment, we might have chosen different experiments to run and more experiments with positive results may have been conducted. However, there are many usability issues that we were aware of but which could not be dealt with in the scope of this thesis. These mainly include functionality connected with the job offer search.

Another improvement in the methodology which could have been made is the evaluation of the results. While we could easily evaluate the effect on the conversion rate using Google Analytics, the evaluation of the effect on usability was problematic. We were not able to quantifiably express the change in usability. After the experiment was finished and the changes were implemented, we compared the Net Promoter Score of the periods before and after the implementation. However, this can lead to misleading results. The major advantage of A/B testing is the fact that the versions are compared in exactly the same environment with the same conditions. When we compare the Net Promoter Score for different periods, we can never know what caused the changes in the behavior. After the implementation, the Net Promoter Score can rise which can indicate that implementing the new changes has led to increased usability. However, there might be other factors such as a new marketing campaign which could affect the score. Therefore, the ideal solutions for our experiments would be to measure the Net Promoter Score separately for both versions while running the experiment. After the experiment was finished, we would not only compare the conversion rates but also the Net Promoter Score. Nevertheless, the implementation of such functionality would be beyond the scope of this thesis. That is why we could only assess the effect on usability based on our assumptions.

To conclude, although some adjustments to the methodology could have been made, we believe that, in general, our methodology was correct. We were able to evaluate all the experiments and draw conclusions based on the results. The iterative approach provided us with the opportunity to learn from the previous experiments and constantly improve the process.

6.2 Validity of the results

We are confident that the resulting numbers for the number of visitors and the conversion rates are correct. For the measurement, we used Google Analytics where we sent the data through the Google Tag Manager testing library by Jorrin Quest[1]. Since the library is open-source, we were able to modify it so that it would fit our purposes better. Although the data collected by Google Analytics are not 100% precise, the deviance is basically negligible. Moreover, all of our experiments used unsampled data. By default Google Analytics uses sampled data after reaching over 500k sessions for the given date. This means that if the number of the sessions exceeds this limit, the numbers in the reports will only be based on a subset of sessions. The traffic on profesia.sk exceeds this limit, having around one million sessions per week. That is why for our experiments we used Google Analytics 360, which applies sampling of 100 million sessions. Therefore, the resulting numbers of users and conversions are precise.

As already mentioned, we were not able to measure the usability changes properly. Nevertheless, in table 5.1, we assigned each experiment with an assessment of the effect on usability. These values are obviously arguable and subject to our personal impressions. We based this number on whether the adjustment actually helped users in achieving their goal. For example, in the experiment *Return to the application form after creating a CV*, the improved usability is obvious. By redirecting the user back to the application form, the user can immediately return to the action which they intended to carry out before they left to create a CV. This adjustment clearly makes the application process easier for the user. Although the ranking for increased usability in table 5.1 is not based on any quantifiable results, we believe that it quite accurately represents the influence on usability.

We also believe that since the results are calculated per user they are more trustworthy than if they were counted per session or per hit. We could have calculated the results of the experiment in absolute numbers (per hit). That means the conversion rate would be measured as the number of times the application form of version A/B was finished, divided by the number of times the application form was displayed. However, this would lead to inaccurate results. There is a distinct possibility that this could lead to a case in which there are a few users in version B on whom the changes have had an extreme effect and who are suddenly sending a high number of applications. The conversion rate would

[1] https://abtestguide.com/gtmtesting

rise significantly for version B which would lead us to think that version B had a positive influence on users. However, for the vast majority of the users, the changes have no effect but the resulting numbers are influenced by the few individuals with irregular behavior. Using per user metric, we can see the actual impact on all the users. Moreover, we can also see the long-term influence better. If the user sees version B but decides to send the application later, provided they do so until their cookie expires, we still count them as a converting user. Furthermore, because the traffic on profesia.sk is relatively high, we were able to see statistically significant results after running the majority of experiments for only one or two weeks. This reduced the sample pollution. There are many types of pollution such as device pollution, browser pollution or cookie pollution. [64] Pollution occurs when a user who has seen version A on one device (or browser) is assigned the cookie for version B on other device. With the longer duration of the experiment, the risk of pollution increases. Since we ran most of the experiments for the shortest period possible (one week), we mitigated the pollution.

To sum up, we believe that the results of the experiments are correct. The metrics and tools used to measure the conversion rates were precise and reliable. The sample size calculator [2] and the Bayesian A/B test calculator [3], which we used, are based on established statistical methods commonly used for A/B testing evaluation. Although there were no data available according to which we could precisely measure the usability changes, we are confident that our assessments fairly represent reality. Therefore, we are able to draw a conclusion on the relationship between usability and conversion rate.

6.3 Comparison with related work

In this section, we will compare this thesis to other related scientific papers. Not only will we compare the results, we will also inspect the difference in used methodology and metrics.

6.4 Comparing the effects of usability on customer conversion and retention at ecommerce websites

The effect of usability on conversion rate was also examined in the paper *Comparing the effects of usability on customer conversion and retention at ecommerce websites.* [65] In the paper, usability was measured based on the IS success model by DeLone and McLean's. [66] The website usability was assessed based on three dimensions: system quality, information quality and service quality. An element of system quality can be, for example, ease of navigation. Information quality captures the quality of content. Service quality represents the overall support provided by the website. The existing instruments were applied to assess the usability of websites Travelocity.com and Expedia.com. 102

[2] https://abtestguide.com/abtestsize/
[3] https://abtestguide.com/bayesian/

students were randomly assigned to one of these websites. The participants were asked to play the role of a customer who wants to plan a holiday in Asia. They were stopped before actually making the purchase. Later, the relationship between the usability dimension and the intention to make a purchase were analyzed. The results showed that all usability beliefs are positively related to the intention to make a purchase. Moreover, the analysis showed that there are differences in effects of various usability dimensions. The perceived system quality has the highest impact on users' intention to buy. On the other hand, the perceived service quality has the lowest impact out of the three usability dimensions. There is a variance of over 70% between these dimensions and the users' intention to buy.

Although the paper presented precise mathematical models to express the effect of usability on the conversion rate, clearly there were a number of limitations. The main drawback is the limited sample size. Moreover, the study was conducted on students and no purchases were made. The fact that the students knew that they would eventually not buy anything could have significantly influenced their behavior. In this thesis, the experiments were conducted on real users who actually made the conversion. Moreover, since they were not aware that they were participating in an A/B test, their behavior was authentic. On the other hand, the assessment of usability is performed more precisely in the paper by Kuan. Therefore, it is possible to precisely define the relationship between usability and the conversion rate.

The results presented in the paper are consistent with the results of our experiments. Although the relationship between usability and the conversion rate in this thesis was not expressed numerically by a mathematical model, the results of the experiments clearly show the correlation between usability and conversion rate. The fact that both studies used completely different methodologies but yielded similar results prove that there is a close relationship between the usability of a website and the conversion rate.

6.5 Website Quality and Consumer Online Purchase Intention of Air Ticket

Another work which examined the relationship between the purchase intention and usability is a paper by Sam [67]. In the paper, the effect of multiple factors on purchase intention was analyzed. The considered factors were: usability, website design, information quality, trust, perceived risk and empathy. For each factor, a hypothesis was developed. For the usability factor, the hypothesis was: *Usability of online website is positively associated with consumers' online purchase intention.* The sample consisted of students and working adults from Malaysia. The study was conducted through a questionnaire consisting of 54 questions covering all of the previously mentioned factors. The questions were mostly aimed at a specific use case of a low-cost carrier service industry. Overall, 208 questionnaires were collected. Again, the results showed a strong positive correlation between usability and purchase intention.

Similarly to the first paper, this paper also used a small sample only. Furthermore, the data they used for proving the hypothesis were collected through a questionnaire and were not based on actual user interactions. That decreases the trustworthiness of the results. Although the results were evaluated accurately using various mathematical models, the methodology used to collect the data was not optimal.

The study by Sam used a completely different methodology from the one used in this thesis and in the previously mentioned paper. Nevertheless, the conclusion from all three studies is the same: there is a positive correlation between usability and purchase intention.

CHAPTER 7

Summary and future work

The goal of this thesis was to answer the question: *Does improved usability lead to a higher conversion rate?* A series of various A/B tests showed that improving usability, especially in critical parts of a website, makes users more likely to convert. Nevertheless, there is still room for further analysis of the hypothesis.

7.1 Future work

The knowledge we gained can be further used to conduct more experiments. By choosing the iterative approach, we were able to learn from previous experiments and adjust the new ones accordingly. After conducting a few experiments, the results were either all negative or we were not able to evaluate the experiments at all. Numerous other experiments not mentioned in this thesis were carried out. Since the experiments showed that increased usability has a positive impact on the conversion rate, we will conduct more experiments in the future to target usability issues and subsequently increase the conversion rate.

To further investigate this issue, more experiments should be run. In future work, more attention should be paid to identifying usability issues. We are convinced that the majority of unsuccessful experiments were due to the fact that they did not actually significantly improve usability. That is why to further prove the hypothesis we would need to run more experiments where we would focus more on improving usability rather than improving the user experience. Nevertheless, we do not want to suggest that improving the user experience does not lead to a better conversion rate. However, the user experience is a more complex concept and therefore the improvements made take a longer time to be reflected in the conversion rate. Furthermore, enhancing the user experience is done through small changes. Shortening the terms and conditions for example, might not yield immediate results. It is only one small part of the user experience *mosaic* which, however, is altogether extremely important. In future research, it would be interesting to measure the relationship between the user experience and the conversion rate as well.

Moreover, in future research, usability should be measurable, so that we can actually prove that it has been increased. This way we would be able to support our hypothesis that the experiments which did not raise the conversion rate also did not raise usability. Mathematical models similar to the ones used in the related works [65] and [67], could be used to precisely express the relationship between usability and conversions. In this thesis, the relationship is only based on our personal impressions. Another possibility would be to measure the Net Promoter Score for both versions when the experiments are running. The results of the Net Promoter Score could then be put in the relation with the conversion rate which would accurately express the relationship.

To sum up, although this thesis suggests a strong relationship between usability and conversion rate, more experiments should be run to support this hypothesis. Such experiments should focus more on identifying the usability issue and expressing usability mathematically.

7.2 Summary

In this thesis, we managed to prove the positive correlation between usability and conversion rate. Although we did not use the term *conversion* in a conventional sense, as a purchase on an ecommerce website, we believe that the results of this thesis are applicable in general to all websites. In this thesis, we analyzed the job portal profesia.sk.

To test the hypotheses, we used an iterative approach and ran multiple A/B experiments. After finding room for usability improvement, we proposed and ranked possible solutions. Afterwards, we developed experiments using Google Tag Manager. These experiments were running for a specific period of time, usually one or two weeks. During this period, if a user visited the subpage where an experiment was being conducted, they were assigned a cookie with the information about the version which should be displayed. For all the experiments, we divided the traffic in a ratio of 50:50. We used Google Analytics to collect the data about the displayed version and the conversion. After the experiment was finished we evaluated the results using the Bayesian A/B test calculator [1]. We implemented version B only when there was a chance of over 95% that the version was better.

Altogether in this thesis, we described 14 experiments. For 6 experiments, the conversion rate for version B was significantly higher than for version A. Although it might seem that in most cases the improved usability did not lead to an increased conversion rate, most of the experiments which returned negative results also had little impact on usability.

Moreover, out of the 14 experiments, 10 were conducted on the application form page. Since the page had a high drop-off rate, we assumed that there must be some kind

[1] https://abtestguide.com/bayesian/

of usability issue. A user survey showed that the main reason for users to leave the application form was that they did not have a CV, which was a required field. This was especially problematic for users accessing the website through mobile devices. That is why we ran the experiment *Optional CV for mobile users*. Although the conversion rate for version B was 6% higher, we decided not to implement version B. For most job offers, a CV is required and an application without a CV is useless. Nevertheless, based on this experiment we plan on implementing an extended functionality through which companies will be able to choose whether they require a CV or not. From the results of the experiment, we can already assure them that not requiring a CV will bring them more applications.

All the experiments which were aimed directly on tackling a specific usability issue were extremely successful in raising the conversion rate. In the experiment *Warning companies before filling out the offer form*, by fixing the reported usability issue, we managed to increase the conversion rate by 17.7%. Moreover, in the experiment *Highlighting an ending offer in the list of bookmarked offers*, version B had a conversion rate that was 10.6% higher. We also implemented the same functionality to the job offer listing where the job offers which are highlighted have a 26% higher conversion rate. Therefore, we also evaluated this experiment as extremely successful.

This thesis also has a number of limitations. These are mainly the insufficient usability problem identification process and the fact that we did not measure the usability of both versions with quantifiable measures. Therefore, we are not able to mathematically express the relationship between usability and conversion rate. Nevertheless, by comparing the Net Promoter Score before and after the implementation as well as from the collected user feedback, we were able to get a picture of the extent to which usability was increased. In future research, we suggest running more experiments where, apart from the conversion rates for both versions, the Net Promoter Score for both versions would also be measured.

In conclusion, through a series of experiments, we managed to prove that there is a correlation between usability and conversion rate. By using the A/B testing method, we can be certain that the changes in the conversion rate were caused by the changes which we made and not by a seasonal trend or a coincidence. Furthermore, since we used established A/B testing calculations and measures, the results of the experiments are indisputable. An essential advantage of this thesis compared to other related papers is the fact that we ran the experiments on thousands of users. The large sample size together with the fact that the users did not know they were being tested increased the credibility of the results. Although we only ran the experiments on one job portal, the diversity of the sample makes these findings applicable for all other types of webpages.

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Glossary

bounce rate Bounce Rate is the percentage of single-page sessions (i.e. sessions in which the person left the site from the entrance page without interacting) [68] . 10

checkout completion rate Checkout completion rate is a percentage of visits that result in an order once the 'checkout' button has been selected.. 10

NPS The Net Promoter Score (NPS) is one of the simplest customer satisfaction and loyality measures, which asks customers only one question on 0 to 10 rating scale: „How likely is it that you would recommend our company to a friend or a colleague?" [45].. 15

order conversion rate Order conversion rate is the number of orders taken divided by the total number of visits during the same time period [69].. 10

p-value The P value, or calculated probability, is the probability of finding the observed, or more extreme, results when the null hypothesis of a study question is true. [70].. 23

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