Optimizing Online Advertising using Dynamic Pricing

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Final thesis for the master's programme
Business Information Technology
At Licentie2GO
28 March 2018

In order to obtain the degree of "Master of Science"
At the University of Twente.

Study information

Programme:	Business Information Technology
Track:	Enterprise architecture

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The publication of this thesis is withhold for a period of 2 years until 28 March of 2020.

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Preface

This report is a representation of my graduation project at Licentie2GO. The graduation project was chosen because of my personal interest in online advertising and e-commerce. After successfully completing the master's course "research topics" with Hans Moonen's guidance, this graduation project is an extension of the research topics project.

In research topics the focus of the project was on dynamic pricing in e-commerce and the current applications of dynamic pricing. This graduation project is extending the research on dynamic pricing with a practical execution of dynamic pricing and the research on effectiveness of online advertising.

Dynamic pricing and online advertising are only a small sub-segment of research operations to be executed in the rapidly changing world of e-commerce. Not only physical commerce is changing (a lot of physical retail stores filed bankruptcy throughout the duration of this research), also e-commerce is changing rapidly. This work is (in my opinion) contributing to the survival of small and midsized organizations in the rapidly changing world of ecommerce.

When looking at e-commerce in the Netherlands; the Top 3 (bol.com, RFS Holding (Wehkamp and Fonq) and Zalando) e-commerce organisations alone (according to Keswiel [15]) had an accumulated revenue of 1824,5 mln. EUR revenue in 2014 but profit margins are very small. These Top 3 stores become larger every year in terms of revenue but not in terms of profit. However, a mid-sized web-shop (or call it: small compared to the Top 3 in the Netherlands) like Licentie2GO is growing similarly fast, but this organisation has to make a profit in order to survive the hard competition in e-commerce without external investors. In the current state of e-commerce on might wonder which aspect is more important; having high revenues or high margins?

This research aims to help Licentie2GO and other mid-sized webshops at optimizing their advertising strategies in order to have more efficient online advertisements. In addition; this thesis is meant to measure values during experiments in a real-business environment such that we can fill a gap in existing literature about online advertising and dynamic pricing.

About the author

After defending this thesis at March 28th 2018, Robbin (RJS) Harleman, is holding a Master's degree in Business Information Technology from the University of Twente. Besides this master's degree, Harleman formally completed the bachelor program in Business and IT at the University of Twente in Enschede.

Harleman founded Licentie2GO (the organisation of this graduation project) in 2014 after a successful 6-years of entrepreneurship in advising small and mid-sized organisations in using IT to support their organisations. During this work, the "problem" Licentie2GO is solving, was found annoying. It was hard to buy legit license keys, have a management-tool to manage those keys for end-clients and at the same time buying from a customer-friendly provider.

Harleman decided to set up Licentie2GO in 2014 in order to make it more convenient and cheaper to buy legal software online. In addition; while the model was growing his vision was to build out the model in such a way that the organisation is advising new customers, is using the big data from the pre-sales and after-sales model to advise and suggest other software packages and let the organisation grow to be the preferred supplier of several hundred thousand clients and small-businesses.

Acknowledgements

In this section I want to thank the people that have helped me complete this thesis and contributed to the contents of this work. Let’s start with a special thanks to my supervisors Hans Moonen and Klaas Sikkel.

Hans, I really want to thank you for the good, substantive discussions we have had. It took a long time from our first contact to the completion of this study, but we have managed to keep in good contact and to make progress in every meeting; Thank you for that. I hope we will meet again for some future work (possibly with other graduate students) or to have contact on a business-level after I have left the university.

Klaas, thank you for your always fast and substantive feedback. I really haven’t met anyone during my study- or during my working life that is responding so adequate and fast on emails (requests and other communication) than you. I appreciate the time you invested in helping me out and especially in the speed and the helpfulness of all your answers.

Last but not least, I want to thank all proof-readers (especially Bernard) and I want to express a special thank you to my colleague Alwin for helping me figuring out how to handle visitor-detection in the most efficient way. It was a major achievement for us together to record millions of visitor-records and at the same time process this enormous amounts of data into incredibly fast analytics.

Management summary

Problem statement

The organisation considered in this report, Licentie2Go, is selling software downloads with legit license keys in a highly competitive e-commerce environment. The organisation is growing enormously because of its investments in online advertising. However, there is no exact measure in place to determine the efficiency of online advertisements. There are statistics about platforms generating an amount of clicks, sales and the conversion rate, but the company isn't able to determine if each platform used for paid advertising is operating on a maximum-efficiency level.

Because of the tremendous costs of online advertising at very small margins per sale, the organisation wants to improve the effectiveness and efficiency of online advertising. Therefore, the goal of this research is to measure the current state of online advertising in the organisation and to find ways for optimizing online advertising using the data found in the measurements.

Literature

In order to optimize the effectiveness of online advertisements, literature defines two major customer groups: strategic- and myopic customers. Strategic customers take into account the current- and all expected price changes while myopic customers immediately decide to buy (or to leave the store) at a detected price change. The strategic- and myopic customers need to be segmented in (as small as possible) segments to optimize advertising tailored to that specific customer segment.

This research is applied on digital products only; these are products that can be compared online based on product characteristics that are non-disputable such as measurements or weight. In order to optimize online advertising (according to current literature), the advertisements need to fit the customer- and product groups. That is; the (operational) advertising strategy needs to fit the current marketing strategy which aims to support the high level business strategy.

Research

This research investigated the current state of online advertising of the organisation. The measurements based on the present data were unable to determine the entire lane from first touch (on the website) to successful checkout. Better measurement-tooling was built and implemented to measure customers' origin in order to apply better segmentation after the transaction was complete. This backwards segmentation appeared to be very useful to optimize the efficiency and effectiveness of pre-sales- and advertising-activities.

Conclusions

Using the newly implemented measurement-tooling, better segmentation could be done. As a result; the organisation could improve its entire offer and pricing tailored to specific customer segments. The offer was improved by implementing dynamic pricing and by matching the advertising strategy accordingly. In addition; the organisation changed the way it was using online advertising: Some platforms used wear generating almost no traffic (while costing money!) while other platforms had undetected potential for attracting new and profitable business. In addition, the tooling build, continuously measures platforms used, in order to make sure to detect and use the potential when variables change. Variables might be internal (such as the pricing of products, review-rating of the business etc.) or external (such as pricing of cometitors' products, review-rating of competing businesses etc).

Contributions and Recommendations

This research contributed to literature by collecting real analytics in an operational mid-sized webshop selling software in the Netherlands and Belgium. The optimizations found and implemented in the business heavily contribute to the businesses' efficiency of online advertising. The business is advised to roll out this model across Europe to use the full potential of the optimizations discussed in this research. In addition; a series of novel insights to literature were presented, accumulating in a set of ideas for future research.

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List of abbreviations

In this section, the most important abbreviations are explained. Please use this section as a reference for reading this paper. In addition, this section might be useful for the reader to get familiar with some background information about e-commerce and dynamic pricing.

B2B-sales	*Business to Business*. A business selling to other businesses.
B2C-sales	*Business to Consumer*. A business selling directly to consumers.
Conversion	A conversion is one realised goal; for example, one successful checkout (a product sold) or one new customer acquired. In this research, most of the time a conversion is one realised sale.
Conversion rate	The percentage of visitors needed for making one conversion.
CPA	*Cost Per Acquisition*; The costs needed to realise 1 conversion. For example, on average 1 on 100 customers is buying a product. In that case, the conversion rate is 1%. The CPA is 100x the CPC for these customers.
CPC	*Cost Per Click*; a method of paying for advertisement (referral-) traffic. Each click on a link is costing money. For example; Google Search Engine advertising is using a CPC model in which each visitor to the website using this advertising is paid to Google. In this example; Google.com is called a referral (see below).
Price-bot	A tool used by customers to compare multiple providers offering the same product at (equal or) different conditions. Conditions are for example price, delivery time, shipping costs etc.
Referral	A referral is a website redirecting visitors to another website (i.e. Licentie2GO.com). For example, when Licentie2GO is advertising on Google, Google is called the referral.
SEA	Search Engine Advertising; paying the search engine to display advertisements on certain keywords. Most often this is a CPC construction (see CPC explanation above).
SEO	Search Engine Optimization; optimizing the website in such a way that it is displayed as high as possible (on chosen keywords) in the search engines natural search results without paying a fee for each click.

1 Introduction

1.1 Motivation

Licentie2GO is a fast-growing mid-sized web-shop selling software downloads with legit license keys. When the business was founded in 2014, selling software digital instead of selling software on a disk was quite a new thing. It solved a problem in speeding up the delivery time. Sending a package to the customer wasn't necessary anymore and customers could download and install their software immediately after the purchase was made. The first version of the platform was built in late 2014, receiving its first customer in 2015. Today, early 2018 the projected annual revenue is over 3,5 million euros.

Licentie2GO is an example of an e-commerce organisation like many others. The organisation started very small, but is expanding rapidly. This fast growth not only effects myself as a managing director and founder of the organisation, but it also effects the employees, the staff, the processes within the business, et cetera.

Most importantly; the business model is changed to support larger volume in number of customers, number of orders, number of support requests, et cetera. The business model which was suitable in the early days, isn't suitable anymore today because the organisation was multiplied several times in terms of revenue, number of products sold, number of customers, et cetera.

1.2 Problem statement

Licentie2GO experiences several problems as a result of the fast pace of growth. For example; despite the revenue of more than 3 mln. euros, there is a very limited profitability. A lot of money is invested in attracting new customers and the business is unsure about the strategy of attracting and retaining those customers. The pricing of products is done based on a competitive strategy of comparing prices in pricebots and also on this decision, no statistics are present on justifying this decision.

Many tech start-up companies face the same problems Licentie2GO faces. However, a lot of those start-ups received growth money or had external investors funding their business plans: Licentie2GO had no external investments nor did the business receive any growth capital. As a result of this; the speed of further growth is depending on the ability to make a profit out of the growing revenue. This research aims to contribute to the growth strategy of the business in order to make a profit out of the growing revenue.

1.3 Research questions

This research discusses the methods, problems and possible solutions that might contribute to making more money out of the growing revenue. In order to get to an answer and a better working solution, research questions were formulated. The main research question, addressing the operational problems of the business and contributing to literature, is formulated below:

RQ: How can we maximize the results of online advertising using dynamic pricing, in a mid-sized web-shop selling digital software?

In order to answer this research question, three sub-questions are formulated. The sub-questions aim to execute this research step by step in order to get the current state of research on this subject to the outcomes of our research question. In the last chapter of this paper, the results of all experiments executed during this research will be combined in answering the main research question.

A platform can be; a website or an app or any other form of online material that is showing advertisements. Most of the time, the platforms are chosen by the business, but sometimes (for example using Google Adwords of Affiliate marketing) all websites connected to Google (Adwords / AdSense) or connected to the affiliate network might choose to display advertisements for “Licentie2GO” on their website.

SQ 1. *What platforms are used to advertise products and how do those platforms contribute to revenue and margins?*

SQ 2. *How can we measure the contributions per platform to revenue and profitability of the business?*

SQ 3. *To what extend can we optimize the advertisement- and pricing-strategies on the platforms used to increase revenue and profitability?*

1.4 Research methodology

In order to create structure in answering the research problems and research questions, this section is handling the research methodology. The goal of following this research methodology is to make this work replicable and to validate the scientific value of the work. A design science study is performed based on the design science research methodology studies of Wieringa [70], Hevner [26] and Peffers [56]. Most importantly, the work by Verschuren en Doorewaard [67] is used in guiding the business experiments (see chapter 5 and further).

Based on the design cycle by Wieringa [70], the structured methodology proposed in Figure 1 is categorised in three stages:

1. Problem evaluation
2. Treatment design
3. Treatment validation

The terminology of Wieringa’s work is re-used in the colour scheme. Besides basing this research on the work of Wieringa, some additions and adjustments are made. Wieringa explicitly suggested a separation between the treatment design and treatment validation phase. In practise this phases may follow up very fast because of a quick iteration in designing a model, redesigning a better model and testing the model in the business which results may function as valuable inputs for improving the design.

The research methodology is schematically showed in Figure 1. The colour scheme is showed in the bottom right where blue is the problem evaluation phase, green is displaying the treatment design where orange is representing the generalisation of the results including the evaluation of results for the business (treatment validation).

The numbers shown in Figure 1 refer to the sections in which the phase will be explained and documented.

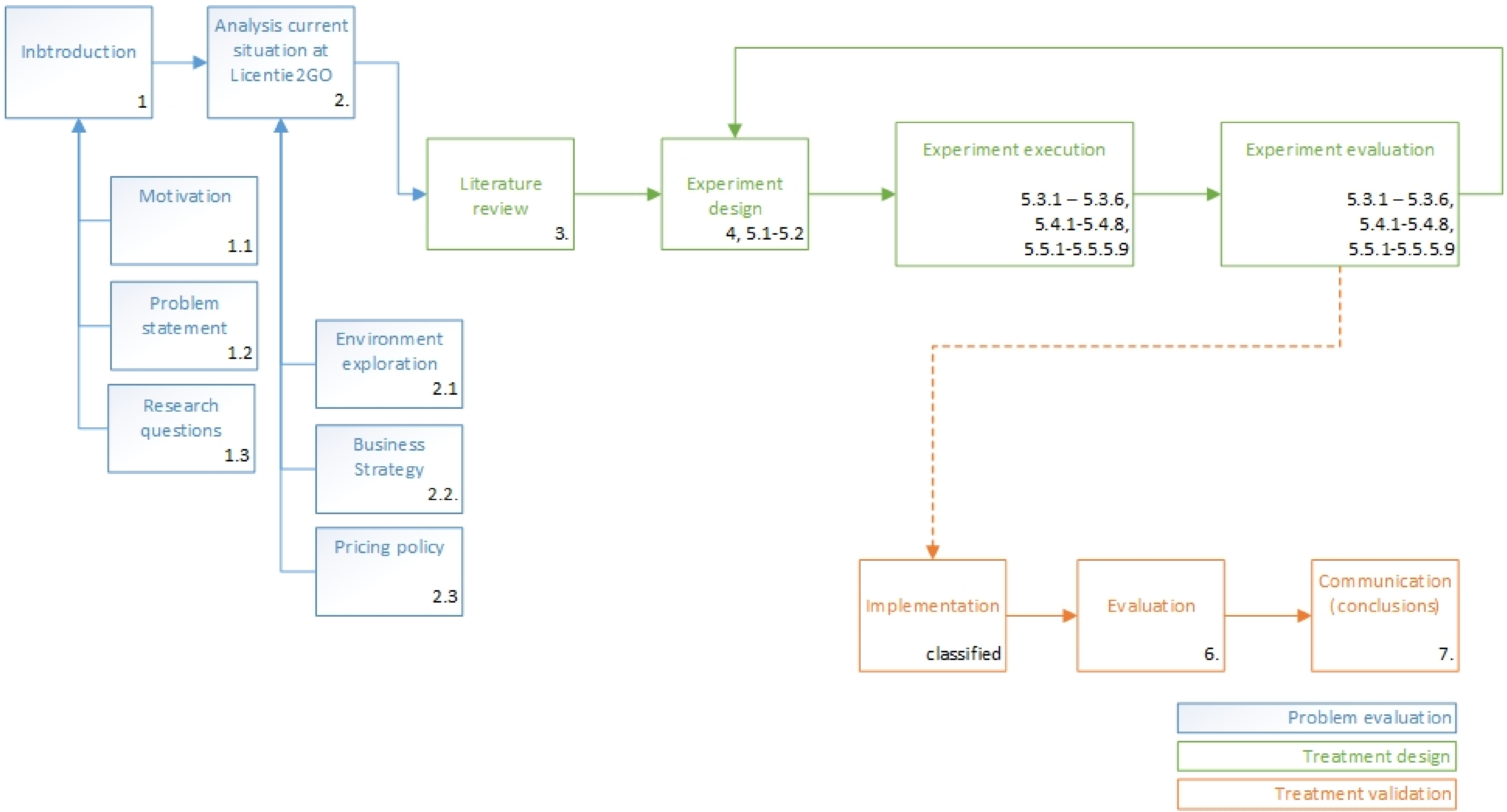


Figure 1 Research methodology

2 The business: Licentie2GO

To make the reader familiar with the business this study is performed in, the business will be introduced to the reader. After introducing the business, the environment in which it is operating will be explained as well as the current pricing policy.

2.1 Environment exploration

Licentie2GO is a web-shop selling software downloads with legit license keys. The external environment of the business is changing quickly. To introduce the reader with the business, the business is explained in more details here. Harleman, author of this thesis is the founder and owner of Licentie2GO.

According to Licentie2GO, the extent to which the organisation (Licentie2GO) is able to respond to those changes is determining the competitiveness and growth of the organisation. Responding slowly or inadequate might reduce competitiveness while a fast and reliable response will increase the competitiveness of Licentie2GO compared to other organisations; New competitors are showing up quickly in the market, pricing are suffering heavy competition making it a difficult market to make money. To organise the efficiency of the process and the focus of the business in perfectly servicing customers using the best set-up of the organisation, the business is marketing two brand names to different customer groups.

Licentie2GO is one of the two brand names under which the larger organisation is operating. The mother organisation is called 2GO Software BV. 2GO Software decided to split the business for selling to consumers from servicing resellers of their products, see Figure 2. The products sold in both businesses are equal; however multiple groups of customers have different requirements which was a valid reason to split up operations. In this research, we will focus on the Business-to-consumer (B2C) brand; Licentie2GO.

More information about the organisation and the strategy behind brand names, can be found in

IP addresses are partly removed because of privacy protection of customers.

Appendix B; Organisation set-up . The resellermodel “Software-Reseller” is out of scope for this research because we did not yet determine the competitive environment of these customers on the reseller-platform. Without knowing competitors (who are the previous suppliers of the clients on Software-Reseller?) and without knowing the competitors’ pricing (previous suppliers’ pricing), any conclusion about the success of the developed dynamic pricing strategy would be unreliable.

Current competitors for the organisation can be found online only. Competitors are businesses selling the same software. All businesses focussing on the same customer groups as Licentie2GO can be considered to be a competitor. Also businesses selling another product but focussing on the same customer group (substitute products). For example;

1. Businesses advertising with “free antivirus”.
2. Businesses selling the same software. For example; Coolblue.nl, Bol.com, Alternate.nl, Amazon etc.
3. Manufacturers selling directly to end clients. For example; Microsoft, Norton, Kaspersky etc.
4. Businesses selling (illegal or second hand-) keys for extremely low prices *. These sellers have a negative impact on the customers’ reference price which determines the “normal price” for a product according to the customer.

* A number of such sellers are on the market today selling but according to Licentie2GO, these businesses won’t be there for a long time. For example; selling Microsoft-software with discounts of more than 75% on the advised sales price is impossible according to Microsoft. According to information from a Microsoft-manager these websites will disappear soon. He said: “Microsoft-lawyers will soon get these websites off the internet and into the court room”. Most of the time – according to Microsoft – these businesses sell software from foreign continents that is unable to be installed in Europe (following the normal procedures). In addition; installing and using such software-licenses is against the license agreement and is therefore to be considered “unlicensed software”.

The next section will explain the business strategy and how the organisation is dealing with such competition.

2.2 Business strategy

Because the intense competition in e-commerce a clear business strategy is needed to survive. Licentie2GO is segmenting these competitors in groups according to the advertising strategy that is needed to compete.

Figure 2 (shown below) is showing the competitive groups and the traffic sources. In addition, the figure shows the costs structure related to advertisement networks involved. The advertisement-networks used can be divided in 4 categories:

1. Price-bots.
2. Advertisement platforms
3. Direct referrals (with offer-display)
4. Direct referrals (without offer-display)

An explanation of the terms used above, can be found in the chapter “List of abbreviations”.

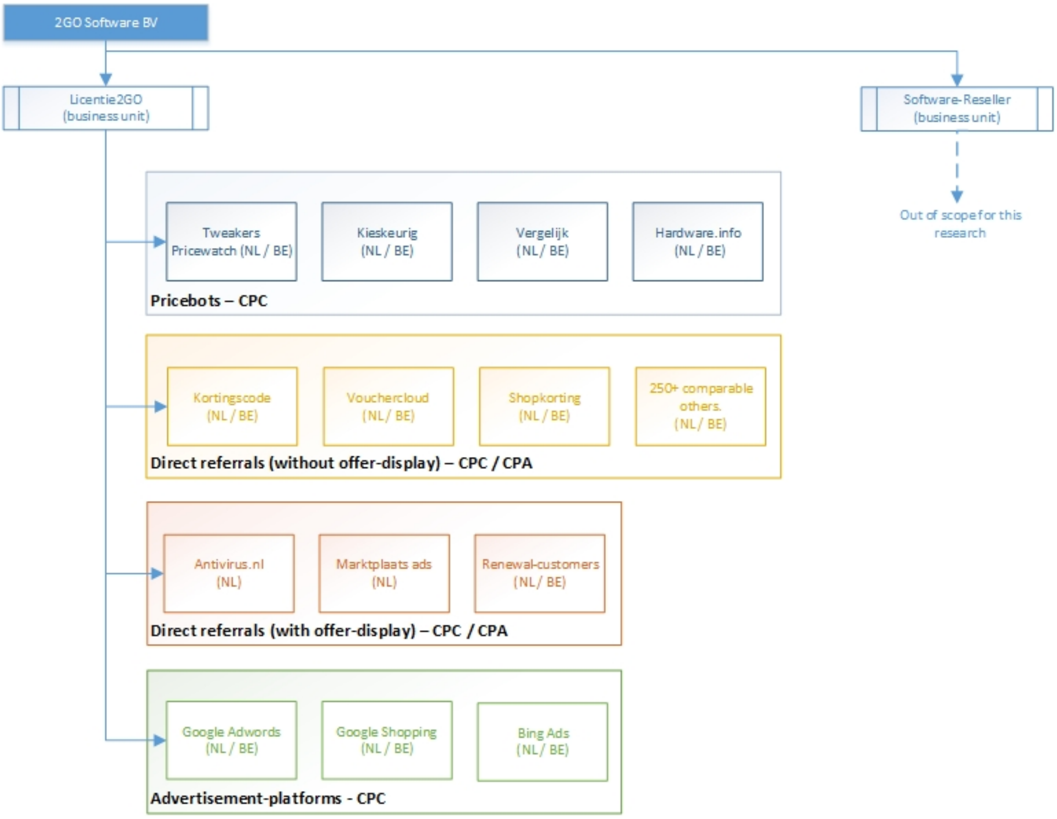


Figure 2 Competitive environment showing advertising networks in the B2C market

2.2.1 Costs structure of advertisement networks.

Important to notice are the different payment methods for the advertising networks. Platforms that are paid on a CPC-base, are paid a fee for each visitor referred to the Licentie2GO-website. Platforms paid on a CPA-base are paid a fee for each conversion.

Pricebot platforms paid on a CPC basis

A price-bot is a platform comparing one product sold at different sellers. The main difference here is price, often accompanied by delivery time and a user-rating of the seller; other unique selling points that sellers might have, are not displayed on such a platform. Visitors can only see those when clicking on the link visiting the sellers' website.

Direct referrals with- or without an offer-display

Direct referrals are platforms referring visitors to the Licentie2GO-webshop. It comes in 2 forms; including an offer-display showing the product offered, including sales price and unique selling points or a referral without offer-display just directing visitors to the Licentie2GO-webshop.

Advertisement-platforms

Last, there is a category advertising platforms. Advertising platforms are paid for direct, adjustable promotion of the web-shop. Promotions can be store-promotions (like; "visit Licentie2GO, click here!", category promotions ("buy antivirus-products at Licentie2GO, click here") or for example product promotions ("Buy McAfee security at Licentie2GO, click here"). Every click is paid since the advertising platforms are all using the CPC-model. The more specific such an offer (from Visit Licentie2GO to Buy product X at Licentie2GO), the more likely it is, a customer is buying a product at Licentie2GO.

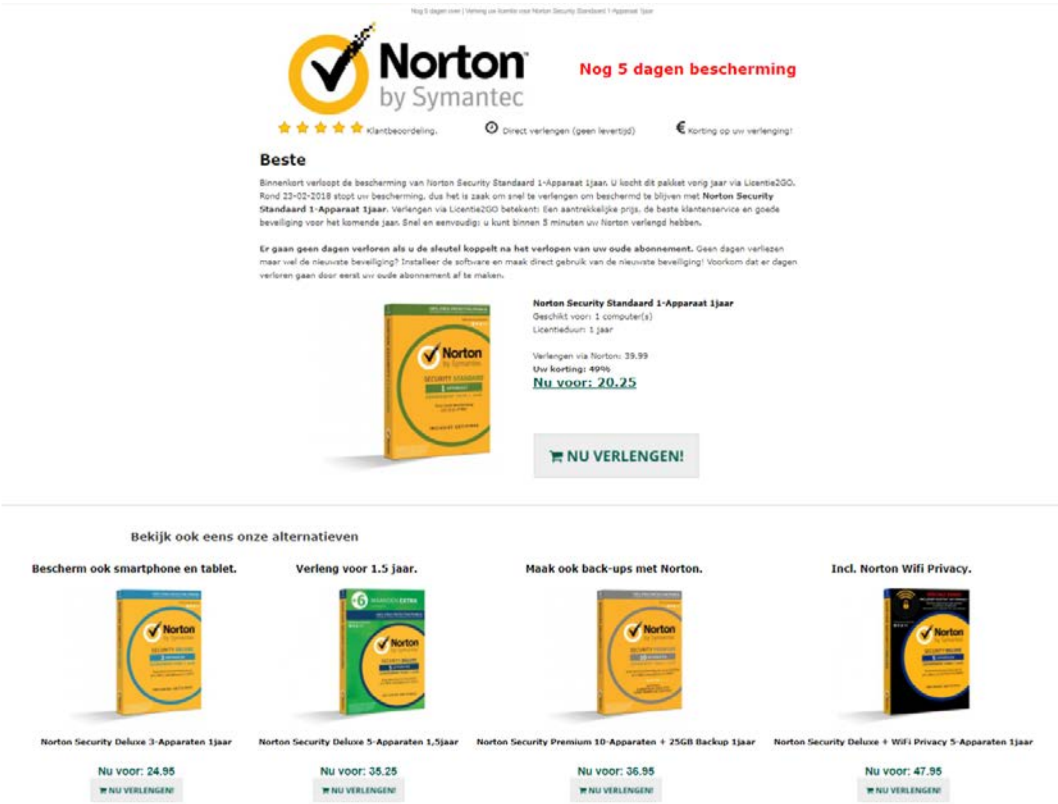


Figure 3. Example of a direct referral (content of a renewal-email)

In the next section, we will explain how the business is dealing with the 4 shown categories in e-commerce. For each category a specific strategy is designed in order have a competitive offer.

Competition on advertising platforms

According to Licentie2GO; Most platforms used for advertising (displayed in Figure 2) can be considered as a competitive environment on itself. That is because of the specific cost structure and because of the internal competition on such a platform.

The competitive element in such an environment is that on most platforms, other sellers of the same product are displayed. The moment other sellers offer the same product, competition arises and the platform can be considered a competitive environment. However, sellers have only limited options to compete. For example; the image below - Figure 4 – shows a listing on the Tweakers pricebot. All sellers compete on having a position that fits their business needs. Sellers might try to have top position (cheapest offer) in order to attract a maximum number of customers. Sellers can also try to have such a price in which they receive an optimum number of customers in relation to the profit they’ll make.

Most pricebots order their listings by default on the total price. Total price is the purchase price of the product combined with shipping costs. In such an environment, the cheapest supplier is listed on top. Most likely, such a top position will result in a maximum number of clicks for this listing.

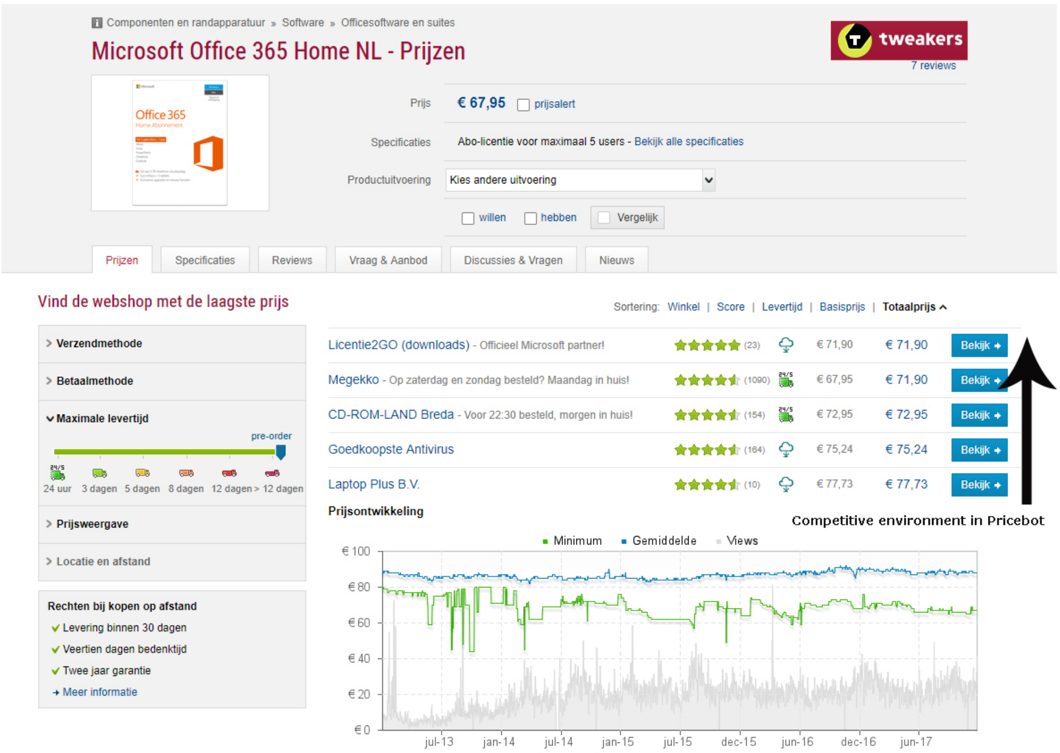


Figure 4. Example of the competitive environment in a pricebot

2.3 Pricing policy in the B2C-market

In the Business-to-consumer-market, the strategy is focussing on customer retention and at the same time at expanding the customer base:

End-consumers. *Competitors:* all other online retail stores selling the same product(s) or at least focussing on the same customer groups. In the business, two separate groups are identified;

a. **New customers;** These customers are not known yet in the business. They are making their first purchase at Licentie2GO.
b. **Existing customers;** These customers are known at Licentie2GO and are (about to) renew their subscription or they want to buy additional software.

According to the business, the most important traffic sources are known, however these sources are not directly reflected in the pricing policy. When asking the business to price changes and the pricing policy, there was a rather simple explanation. The pricing policy customer-based on specific customer groups is explained by the business as:

1a. Prices are adjusted based on competitive action. However, margins are not calculated after a price adjustment, prices are publicly visible and competition is fierce. Sometime prices are adjusted multiple times a day.

1b. Prices are undercutting competitors' price. In order to retain customers, know clients are offered a lower price. This price is most often undercutting prices of our competitors.

The question for this thesis to answer is; how to optimize the pricing policy to better fit the businesses' needs. The research questions are formulated in such a way that literature is analysed to use state of the art theories and combine them with real analytics from the business.

The next chapter is handling literatur. The experiments in order to design a better model for the business is worked out later in Chapter 4.

3 Literature study: Advertising & Dynamic pricing

In this chapter we will look at the current state of literature around dynamic pricing, advertising, segmentation and other related research fields. The literature study will start broadly by looking at state of the art literature on **online advertising**, the research field of **dynamic pricing** and important subjects around **e-commerce**.

First, the definitions used in this research are set out. Definitions are of major importance because they determine the boundaries of our research. In addition; definitions are set because we want to make sure, the theoretical definition is matching the operational situation at Licentie2GO.

Later, in section 3.2 an overview of the current state of literature on our subject is presented. From the current state of literature, we will absorb available knowledge and use that knowledge in order to define experiments on unanswered questions in literature. The experiments will be executed at Licentie2GO; the business that is subject of our study. In chapter 4 the translation from literature to experiments will be worked out.

Definitions

A literature research is performed in order to answer the research questions introduced in the previous chapter. To build a model of influencing variables around the research question, the model construction starts with defining terms that could not be defined in the previous chapter because we want to re-use definitions from existing literature and the definitions need to match previous theory and the workflow of the business (Licentie2GO). To define the environment, definitions of the following subjects will be introduced:

1. E-commerce
2. Digital products
3. Non-digital products
4. Dynamic pricing

3.1.1 E-commerce

The aim of this research is to focus on dynamic pricing *in* e-commerce instead of performing 2 separate researches on dynamic pricing and researching e-commerce. Because of this, e-commerce is not a research field on its own, but we re-use existing e-commerce literature were needed. E-commerce characteristics are incorporated in this research as much as needed, that is (dynamic) pricing *in* e-commerce, and pricing characteristics of e-commerce, but e-commerce as a whole is not a research subject. E-commerce is considered the enabler for dynamic pricing and measuring their results [31].

E-commerce is defined by using Wikipedia [17]. Performing an extensive literature search to find the best matching definitions is a waste of time, considering the fact that e-commerce is only a small part of this research.

E-commerce

> a transaction of buying or selling online by using a website or online marketplace without direct contact between buyer and seller.

3.1.2 Digital products in e-commerce

Besides the fact that e-commerce is subject of research, the focus is narrowed in this section using the research by Lal et al. (1999) [5] and Harleman (2016) [25]. In this research, the focus area of e-commerce is on "digital products". The concept of digital versus non-digital products is not new. Nelson [52] introduced a comparable definition already in 1974, however in that time the definition was for physical stores (not for e-commerce). Products with non-digital attributes where called "experience" goods where digital products where referred to as: "search goods". Digital products have attributes which are measureable and cannot be discussed or debated. Food (is non-digital) can be debated, tasted and evaluated differently by every consumer, but the metrics of a tablet-screen (digital product) and the storage size of the tablet are fixed and cannot be discussed. The brightness of the screen of the tablet however, is another non-digital attribute.

Digital products

> Digital Products are products with attributes that can be compared easily online; like dimensions, weight, name etc.

Non-Digital products

> Non-Digital Products are products having mainly attributes that are disputable and therefore hard to compare online. For example; colour, flavour, smell, sound etc.

The distinction between digital and non-digital products is important because of the process of choosing and buying a product online. If a customer for example wants to buy a non-digital product, let's say a coffee machine, he can buy it online and is able to compare the digital attributes of multiple coffee machines. However, when visiting a store and tasting the coffee, maybe the customer decides to buy the machine with less positive digital attributes because the taste of the coffee is better. When a product with more non-digital attributes is compared and bought, the search online can be different from the search offline. Because the interference of non-digital attributes is difficult to measure, this research is focussing on digital products in e-commerce.

By defining "dynamic pricing" based on literature, a quick literature review reveals that multiple definitions are used. Probably the most important reason for different definitions is that when looking at previous work, one will find several important research about dynamic pricing itself and subjects near to dynamic pricing. All definitions from related work can be helpful because they provide insight in combinations of product pricing and other research fields. This is because, product pricing can never be an activity on its own, but is to be performed with a certain strategy. The same is with the related research fields on its own. For example, the marketing strategy needs to be in line with the business strategy, otherwise it will never produce a successful marketing campaign. The same is with product pricing; it needs to be in line with the business strategy.

To come to a working definition of dynamic pricing for the remainder of this thesis, we will use overview research work of Boyd [9], Elmaghraby and Keskinocak (2003) [18] and den Boer (2015) [8] because they mapped existing literature, looked at dynamic pricing already implemented in some branched and mentioned a number of related subjects above in relation to dynamic pricing. In addition, the authors argue that there is an influence from the related research above on dynamic pricing which can be divided in a number of categories. The categories and related work are introduced in the next chapter.

Based on [8], [18] and [19] the working definition of dynamic pricing for the remainder of this thesis is described below.

Dynamic pricing

> Dynamically allocating the price for a product or service to be sold to a group of customers with a known demand rate in order to achieve a predefined goal.

In which:

- The demand is flexible based on price, history, product life cycle or other variables;
- All **customers** in the group (segment) fit the predetermined attributes of the segment;
- **The product** has a procurement price and a **devaluation rate**
- **Price** should be set in the dynamic pricing strategy in line with (the) predefined goal(s). The goals can be of all kinds, like marketing, business-growth, customer retention, inventory devaluation etc.
- The **capacity** of products or services to be sold is fixed or a new amount can be re-ordered to inventory
    - At a known procurement price
    - With a delivery time
    - And holding costs

3.2 An overview of literature on dynamic pricing

To start the literature study on dynamic pricing, some overview papers are gathered to look at the current state of literature. The work of Elmaghraby and Keskinocak (2003) [19], Bitran [7] and Den Boer [8] give a good overview of the work already published on dynamic pricing (see Figure 5). These papers are selected because of their vision on e-commerce and because they reflect on the past. The overview they all 3 together present, is a starting point for dynamic pricing in e-commerce.

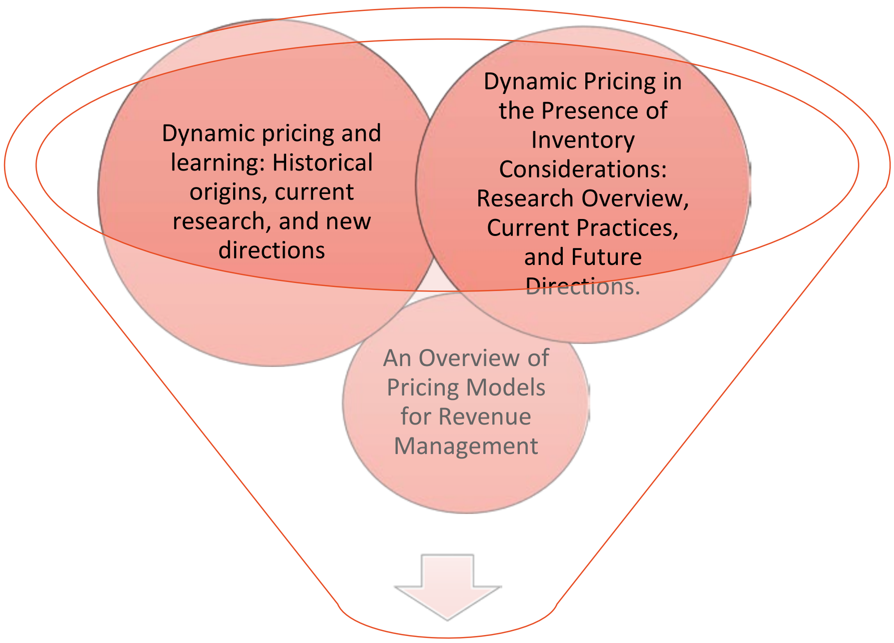


Figure 5 Overview-papers in literature on dynamic pricing

Besides the fact that those researchers also touch the related subjects mentioned in the previous chapter, the researchers indicated that literature indicates 3 important elements in dynamic pricing which influence the method of pricing and the way results of pricing are influenced: inventory, demand and customer.

Based on the overview of research by den Boer, Elmaghraby and Keskinocak and the papers mentioned on dynamic pricing and related research fields, the research area is modeled below in Figure 6. The image shows that dynamic pricing is never a working field on it's own within the business. To make a dynamic pricing strategy work for the business, dynamic pricing should always be supported in other layers of the business. The alignment of such a strategy can be compared with any other form of business strategy. At the top – in high level management – strategy is set out. In all layers below, the strategy becomes more concreted and worked out at differend levels of management. In this case; dynamic pricing is an operational strategy which should suit the high level business goals.

Figure 6 Overview of research field of dynamic pricing in literature

Literature overview on e-commerce & dynamic pricing

In order to design an improved dynamic pricing strategy, more information about dynamic pricing and about product pricing is required. A literature study is performed on these subjects in order to make sure the improved dynamic pricing strategy is supporting the high-level business goals in the business of our subject. To guide this research on completeness, an overview of the subjects is shown below. Each section with state of the art knowledge is worked out later in this chapter.

Most researchers working on dynamic pricing, already refer how they designed their research and how to fit their research in the business layers to support current operations. In order to learn more about these subjects, our literature study found a number of papers on important research subjects: Related research fields found in our literature search are Business-strategy related researches such as revenue management [19], but also:

1. **Dynamic product pricing** and **Pricing strategies** in e-commerce under inventory considerations: [5], [10], [12], [19], [27], [34]
2. **Optimizing online advertising** and **sponsored search (SEA):** [20], [72], [55], [30]

3. **E-commerce** characteristics on dynamic pricing & reference pricing: [47], [2, 52, 53], [62]
4. **Segmentation, Product attributes** and **product family pricing**: [64], [38], [34], [53], [52], [45], [59], [60]

3.3 Dynamic product pricing and Pricing strategies in e-commerce under inventory considerations

In order to learn more about product pricing and pricing strategies in e-commerce, the work by Lu et al. [42] about a "joint pricing and advertising strategy" is a starting point. This work combines the factors mentioned before in a combined strategy; dynamic (promotion) pricing, advertising strategy and reference pricing/willingness to pay. The basic assumption in this research is that consumer demand can be influenced by adjusting the level of advertising and the sales price (in other words; demand is price sensitive). A combined pricing and advertising model is developed to influence the number of sales in order to maximize profits. During this strategy, measuring the results is needed in order to develop an optimum under which the profit is maximized under the level of advertising for a certain (promotion) sales price.

Such an optimum can be developed in all kinds of advertising platforms. The work by Liu et al. [41] give a first overview which incorporates the Click True Ratio (CTR). This CTR is the first basis of finding an optimum in pricebots or price comparison tools. Those platforms can be seen as a standard auction Dutch auction in which a basic price is set and the auctioneers strive down the price until a buyer is willing to buy at the lowest price. Several general strategies for winning such auctions are to be found in literature [40], [65], [49], including some more specific strategies such as winning an e-bay auction [44].

Combining the auction theories with the optimum model by Liu, several extensions are possible. Zhang et al. [73] combined dynamic promotion pricing with demand and inventory control. In such a model, the auction on the pricebot and the advertisement strategy can be adjusted to sell the current inventory at a maximum profit level.

3.3.1 Influence of time on demand and inventory

Time is an important factor in modelling demand and inventory. First, the inventory may have a devaluation which means the products lose value over time as long as they are inventory [7, 19, 35, 53]. For example, vegetables in the grocery store. In the airline industry, we already saw prices of a flight varying based on the time between the first ticket sold and the flight taking of [33, 47].

Another form of devaluation heavily used in consumer electronics, is the product life cycle theory. The theory not only describes devaluation during the product life, but also optimal inventory levels for products in their lifetime.

3.3.2 Product life cycle theory

The product life cycle theory (by Vernon [20]) is all about introduction and growth of new products. This also applies to re-launching new models of the same product. One can easily observe that every now and then for example a new version of the VW Golf car is being launched. This is a perfect example of the product life cycle in the growth phase of a re-launched product.

The most important characteristics of the product life cycle for this research are summarized in Table 1. Important to note here is that price of a product is depending on the aging of the product. In the maturity phase, product price should be on its lowest point. However, when introducing a new product, prices are still high because of high investments in marketing and branding / building awareness for the product (and in new brand launches: the brand).

An important note in the product life cycle theory is that there is more than just a relation between price and demand. Demand should be encouraged by marketing activities and promotions and be supported by product pricing. All in all, there should be a fit between elements from the product life cycle theory in order to generate maximum revenue from the product.

Table 1 Product life cycle summary.

	INTRODUCTION	**GROWTH**	**MATURITY**	**DECLINE**
PRICE	High	Lower	Lowest	Rising
STRATEGIC FOCUS	Expand Market	Penetration	Protect / Innovation	Productivity
MARETING OBJECTIVE	Build	Build	Hold	Harvest / manage for cash / Divest
PRODUCTS	Basic	Differentiated	Differentiated	Rationalized
PROMOTION	Creating awareness / Trial	Creating awareness / Trial / Repeat purchase	Maintaining awareness / repeat purchase	Cut / Eliminated
BRAND OBJECTIVE	Product awareness / Trial	Brand preference	Brand loyalty	Brand exploitation
DISTRIBUTION	Patchy	Wider	Intensive	Selective

3.3.3 Relation between demand and inventory

The relation between demand and inventory is discussed heavily in literature in combination with dynamic pricing [6, 35, 48, 58]. Most of the literature is about a fixed amount of inventory which should be sold in a single selling season under unknown demand. This problem is called; the newsvendor-problem. The newsvendor problem is evaluating a perishable product. The newspaper loses its value at the end of the day when unsold. Therefore, newsvendors should optimize their daily profit by selling as much newspapers in the morning and during the day they should evaluate their inventory in order to decide which pricing strategy should be best to make the most money out of the remaining inventory. Of course; before the selling of newspapers is starting, the newsvendors should evaluate the ideal number of newspapers to produce [57], [2], [54]. The newsvendor problem can learn how to deal with an unknown demand under a fixed inventory. This learning experience may be useful for every seller using dynamic pricing on products that are end of life, but for the rest of this research we consider this problem out of scope because inventory is replenishable in the business the thesis is performed in.

3.3.4 Inventory considerations in dynamic pricing

The work of (2003) [19] and den Boer [8] will be re-used to create structure and guidance and evenly important to make sure that we don't re-do previous research, but to add to previous research. Their work presents a reusable categorization of the literature about dynamic pricing. The categories are based on 6 distinctive elements. They are introduced and (briefly) explained below:

1. **Replenishment** (R) vs. **No Replenishment** (NR) of Inventory. It means a lot for pricing decisions if the stock can be replenished during the selling period. Usually, pricing decisions need to be made before the selling starts if the stock cannot be replenished. In addition; most of the time the selling period is shorter in NR-selling environments.

2. **Dependent demand** (D) vs. **independent demand** (I) over time. Seasonal products appear to have another selling-approach compared to non-seasonal products.
3. **Myopic customers** (M) vs. **Strategic customers** (S). “A myopic customer is one who makes a purchase immediately if the price is below her valuation (reservation price), without considering future prices ”[19]. A strategic customer takes into account all (possible) future price changes.

Based on the distinctive elements above, the work of Elmaghraby and Keskinocak [19] follows by creating categories based on a collection of elements. Despite the fact that 8 combinations are possible by combining all 6 elements above, only NR-I-M, NR-I-S and R-I-M are worked out. The authors argue that only these 3 categories cover the applicability in most markets and the adoption of dynamic pricing in practise.

3.4 Optimizing online advertising and sponsored search (SEA)

Online advertising is worth multi-billion euro’s worldwide. There are multiple researchers that researched the relationship between product pricing and online advertising (most of the time: sponsored search advertising). Sponsored search is probably the most used online advertisement mechanism. A lot of research in published about winning a broad match auction in search engines [20], [68], [21]. The largest sponsored search mechanisms in Europe (Google Adwords and Bing ads) use a Vickrey auction, also called “second price auction” in which the second highest bid is to be paid by the one placing the winning bid to prevent exponential, extreme advertising costs for the winner of the auction.

Most search engine offer sponsored search in which an advertiser can place a bid on a keyword and in result, an add is shown. All engines use another strategy to determine which add is shown, for example the highest bid / the bidder with the highest quality add / the add best matching the search keyword etc. Google and Bing released the fact that they use a Vickrey auction, but the auction is only a small part of winning the highest, best viewed, add position if we incorporate quality of the add and keyword match.

The work by Lu et al. [42] about a “joint pricing and advertising strategy” combines the factors mentioned before in a combined strategy; dynamic (promotion) pricing, advertising strategy and reference pricing/willingness to pay. The basic assumption in this research is that consumer demand can be influenced by adjusting the level of advertising and the sales price (in other words; demand is price sensitive). A combined pricing and advertising model is developed to influence the number of sales in order to maximize profits. During this strategy, measuring the results is needed in order to develop an optimum under which the profit is maximized under the level of advertising for a certain (promotion) sales price.

Such an optimum can be developed in all kinds of advertising platforms. The work by Liu et al. [41] give a first overview which incorporates the Click True Ratio (CTR). This CTR is the first basis of finding an optimum in pricebots or price comparison tools. Those platforms can be seen as a standard auction Dutch auction in which a basic price is set and the auctioneers strive down the price until a buyer is willing to buy at the lowest price. Several general strategies for winning such auctions are to be found in literature [40], [65], [49], including some more specific strategies such as winning an e-bay auction [44].

Combining the auction theories with the optimum model by Liu, several extensions are possible. Zhang et al. [73] combined dynamic promotion pricing with demand and inventory control. In such a model, the auction on the pricebot and the advertisement strategy can be adjusted to sell the current inventory at a maximum profit level.

3.4.1 Bayesian strategies

In online advertising every business is aiming to win the game of maximizing his revenue, maximizing profits or achieving another goal. The fact however in experimenting with dynamic pricing in practise is that one should consider that every strategy is a Bayesian strategy; we assume imperfect information and design than the experiment. However, because of the imperfection in information about the game and the results, we also don't exactly know the strategies of competitors competing in the game. To work with Bayesian strategies, we should assign a random variable in every strategy to make the imperfection disappear because every player has the imperfection in it (based on [12]).

When we consider the nash game of dynamic pricing, every player in the nash game is following a strategy. The strategy should be in line with the business strategy in order to achieve the business goals. For example; A manufacturer like Apple is unlikely to implement a heavy dynamic discount strategy (market penetration) because business goals of Apple likely are building a strong brand. Products are expensive and the brand name is heavily paid for. Implementing a strategy of dynamic pricing and cross selling (diversification) in order to achieve the business goals is far more likely for Apple.

3.5 E-commerce characteristics on dynamic pricing & reference pricing

Using a webshop to sell products is in some case comparable to selling products in a physical store. For example; there is still a customer (buyer), a shop (seller) and a product involved. However, for e-commerce for example it is much easier to compare prices from 10 stores instead of comparing prices of 10 physical stores. In addition, webshops might visualise products differently while a physical store is able to just present the real product in the store itself. Such characteristics might have advantages, but might also have some disadvantages. This chapter is discussing these items in order to make sure the reader is familiar with the concepts and is able to have a critical view to e-commerce and the pricing strategies in e-commerce.

3.5.1 Webrooming & showrooming

Teixeira and Gupta wrote in the Harvard Business Review [64] about trends that push or limit e-commerce sales; webrooming vs. showrooming. The authors saw a trend of showrooming (viewing the product in physical stores and buying online) and webrooming (viewing the product online and buying in physical stores). The authors describe a strategy of changing the products in such a way that they are harder to compare online. For example, mentioning the series of the product instead of the full name or registering own product EAN or SKU codes.

Without judging the strategy (making it harder to compare products) entrepreneurs should ask themselves if they sell the product in a way they should sell their products. In other words; is there a fit between marketing, approaching the customer segment in the right way (online or offline) and does the product match the way of selling. The distinction between digital products (suitable for online sales) and non-digital products (less suitable for online sales) is very important in this.

3.5.2 B2B-Shopbots & Pricebots

Kephart [36] describes some strategies that can be used by shopbots when used for one-to-one negotiations in a B2B environment. The theories below can be used for buying, but also for selling products. In practise, theories can even compete against each other. The importance of a winning strategy was clearly described by Hopkins & Seymour [28]: "It is a common experience to find that prices vary between different sellers, giving consumers an incentive to search for low prices”. Consumers will search for lower prices as long as they have a common product sold at multiple sellers.

Theories for shopbot-strategies decribed by Kephart [37] are:

- Game Theoretic (GT) price computation. Sellers do not observe another sellers price before they set their own price. Prices are set randomly from a distribution f (p) which is the expected price range (min-max price) of the product according to the buyer. The GT-strategy is searching for an optimum price. This search is helped by setting random prices. The correct price will generate the most revenue and will be the price for the remaining time of selling the product.
- Myopically Optimal-strategy (MY); also called Best-response cournot algorithm. It requires knowledge of all prices of competitors offering the same product. Prices are set in response to competitor prices at a level that will maximize short-term profits until a competitor changed its price. That is the moment that prices are re-calculated and new prices are set.
- Derivative Follower-strategy (DF). This strategy experiments with incremental increases (or decreases) in price. At the same time measuring profitability. Price changes are continued until the moment that a drop in profitability is measured. At that point the price change is reversed to maintain the maximum profitability level. This strategy requires the least computation power and the least information about the competition. This strategy is just increasing/decreasing prices till the optimum is reached.

To avoid a race to the bottom for the lowest price “Sellers might avoid undercutting if they could foresee that it might invite retaliation”. That is; the learning effect of the shopbot strategies is of major importance to make sure that the strategy is smarter than just undercutting prices [50].

Besides the pricing strategies above, businesses might have other reasons to change the price of products. For example to introduce products to a new market or to have a price that will fit the lifetime of a product (see also: product life cycle theory in section 3.3.2).

The Ansoff matrix is describing a growth strategy for products in relation to the market in which the product is being sold. The table below is summarising the model. To explain the model in more detail, the 4 growth options are explained.

1. **Market penetration.** Market penetration can be done for example by gaining customers from the competitor or by selling more products to existing customers. Organisations often use promotion pricing to gain more customers or even buy competitors. Apple would never do this, but Philips was manufacturing MP3 players at low prices to penetrate the market in the early days of MP3 players.
2. **Product development**. Product development is developing new products for existing markets. This can also be a new variant of an existing product. For example, Apple first launched the iPod and later on they launched the iPod Nano, iPod mini, iPod Shuffle etc.
3. **Market development**. Market development involves launching existing products in new markets. For example, the launch of Apple’s iPod in Europe (after a successful launch in the USA) is a form of market development.
4. **Diversification**. Diversification is producing / manufacturing new products for new markets. The introduction of the iPod by Apple is a form of diversification. It was a

totally new product in a non-existing market (until then the only mobile music player was the Walkman or Discman).

	EXISTING PRODUCTS	**NEW PRODUCTS**
EXISTING MARKETS	Market penetration	Product development
NEW MARKETS	Market development	Diversification

3.6 Segmentation, Product attributes and product family pricing

Segmenting customers into groups with common interests is a methodology heavily used in marketing- and product development. The aim is to achieve a fit between the product sold and the customers' needs. Achieving such a fit may not only results in a more satisfied customer, but also in increased margins because of the increase in sales because of the fit, but also because of the increased willingness to pay caused by the better fit [43].

3.6.1 Segmentation in the airline industry

In order to learn more about segmentation, literature is writing a lot about dynamic pricing and segmentation in the airline industry. According to [33] some airlines have up to 15 different prices for the same seat in an airline. The prices may vary because of time and conditions on which the seat is booked (restricted / unrestricted), including meals, including priority boarding, including extra leg-space etc. The segmentation because of time of booking, is in this thesis considered as changing the price because of inventory / demand rates, but a change in product to better fit the needs of the customer, is clearly proven with up to 15 different prices for the same seat based on the conditions of the booking.

Besides the little change in the product configuration, a good example of segmentation (used today) can be observed in the automobile industry. The price of a new VW Golf with a certain engine is for example X. However, that price is without any options. For every option needs to be paid extra. Options for business people are "segmented" in a group. For example; the VW Golf business edition which includes several options for a fixed extra price. However, the business edition is a standard package of options for a standard price. No discount should be given if one wants to order the VW Golf business edition without air-conditioning for example. The care is heavily changed according to the demands of the customer segment.

3.6.2 Defining segmentation for this thesis

Kambil and Agrawal [33] describe segmentation as: "Segmentation and rationing exploit the difference in the willingness of customers to pay through different channels, at different times and with different levels of effort. To use these strategies, companies must create specialized product service bundles priced according to product configuration, channel, customer type and time". Important customer types are strategic versus myopic customers [58], [19]. The myopic customer is buying the product immediately after the price is below his/her reference price. In contrast; the strategic customer is also considering future price changes.

The research by Gönsch et al. [24] described several strategies for dealing with strategic customers. Of course, one can imagine that strategic customers are harder to deal with than Myopic customers because strategic customers guess future price changes and include then in their purchase evaluation. An interesting strategy they mention is "price matching" which is actually used in one of the largest Dutch grocery stores (Jumbo). If a competitor is offering the same product at a lower price, the price difference will be refunded. Gönsch et al. suggest that the refund also should be paid out if the supermarket itself dropped it prices sometime after the purchase was made.

3.6.3 Reference price research

The work by Mazumdar [46] gives a good overview of the research that has been done on reference pricing. A conceptual framework is introduced in which several moderators and effects of the reference price are introduced. The formation of reference price is explained as well as how to use reference price in order to influence purchase behaviour.

3.6.4 Product family pricing

Dolgui and Proth [16] describe a business-economic approach to product pricing. They argue that price can be helpful in realising business goals and increasing competitiveness. They describe that the pricing strategy should fit the business because a fitting strategy can increase the competitiveness of the business. A brand selling top quality products (i.e. Maserati) should never use a promotion pricing strategy decreasing its prices. Instead, a fitting strategy should be to increase product value for the same price. This business and economic approach is a form of strengthening the business strategy by implementing the right price which is resulting in an overall better performing business because consumers will recognise the fit.

Within product family pricing there should be a distinction between substitute products and complementary products. Kachani and Shmatov [32] describe and calculate pricing implications of these terms within product families. Complementary products reinforce each other and are therefore perfect candidates for being sold together (cross-selling) or sold as an upgrade (upselling). Substitute products substitute (as the term suggests) another product. This can be an alternative brand or a plastic bottle substituting soda in a can for example.

Multiple authors white about cross selling, but the work of Netessine [53] applies cross selling and dynamic pricing together. In that case a first product is used for advertising because of the great deal; the product should attract new customers. A second product is inserted in the product family to be sold together with the first product. In this scenario, the first product is sold break-even or sometimes with a loss, the second product is generating the margin.

3.6.5 Product pricing from a marketing-perspective

Shapiro and Jackson [60] (marketing-researchers) published a paper in the Harvard Business Review in 1978 about pricing strategies. They provided several insights in the marketing field, but also 3 strategies for price setting.

1. Cost-plus pricing: the costs of production and a “plus”; the margin on the sale.
2. “Follow the leader”: measure competitors price and match or beat those prices.
3. Customer-based pricing approach. Later on this method of product pricing was called “segmentation pricing” in literature.

To start off with the first item “cost-plus pricing”; costs in this matter means: the total cost of manufacturing and selling a product. Off course, including procurement of components and parts for manufacturing, advertising and transaction- and shipping costs.

“Follow the leader” pricing in the time of Shapiro and Jackson was based on following the price of nearby stores in the shopping district. In that time (1978) it was impossible to follow prices of every competitor. Today, in the e-commerce era it is easier to measure prices of more competitor for less costs (and less time) and thus it is easier to follow more competitors in their pricing strategy.

Segmentation pricing is a more complicated pricing theory. Shapiro and Jackson argued that customer groups can value aspects of a product in different ways and that products should be priced differently based on the different configurations.

3.6.6 Product pricing from a high-level business approach

Besides all known strategies mentioned in the previous sections, literature introduced a number of situations for product pricing designed from a top-level business approach. For example the work by Dolgui and Proth [16]. Table 2 shows the pricing methods discussed by introduced by Dolgui and Proth [16] and the reasons why businesses apply such a strategy in a certain situation. The study by [16] is extended by example companies or products which are using the pricing methods in the table to make the examples useful for our further research.

3.6.6.1 Product pricing categories from literature

The authors Dolgui and Proth [16] argued that pricing can heavily influence operational results (see introduction chapter). However, the choice for a pricing method for example low pricing or penetration pricing depends on the operational goal. To explain this in more detail, the terminology of posted pricing mechanisms used in the paper by Harleman [25], is re-used, but is slightly changed to work out things in more detail. The terminology used below are based on the categories proposed by Soon [61] and Harleman [25];

1. Static, non-competitive pricing.
2. Dynamic, non-competitive pricing.
3. Dynamic, competitive pricing.
4. Dynamic, customer-oriented dynamic pricing.

Static non-competitive pricing
Pricing models in this category used fixed pricing of products. The fixed price can be set for one product or for a set of products (to introduce a price ratio between a number of products). The pricing is fixed based on product costs + margin. Margin can be designed in several ways.

Dynamic non-competitive pricing
Dynamic pricing models are the ones in which the prices are set fixed at time t=0 but is subjected to price changes in the future; the price varies from time to time. The non-competitive element in this pricing category refers to the nature of price changes. Prices are changed for example because of perishable goods are priced or because of a short of stock for a certain product. The basis of this category is that price changes are not the initiated by an action of the competition.

Dynamic competitive pricing
This category can be compared to the previous one (Dynamic non-competitive pricing models) with the exception that prices are change because of actions taken by competitors. “As the word ‘competitive’ suggests, each seller’s objective depends on his and other sellers’ decisions” [61].

Dynamic customer-oriented
This form of dynamic pricing (red: customer-oriented dynamic pricing) is relatively new. The reason for the dynamic pricing is the customer itself. Based on numerous elements that are observed in the customer (on the Internet this is easier than in a retail store), prices are changed. However, this category is not reserved for online-use. In a physical store prices may be changed for specific customers for multiple reasons; for example, using multiple brands, giving customer-specific discounts etc. For example; all large national opticians (Eyewish, Het

Huis, Hans Anders, Specsavers and Pearl) in the Netherlands are owned by one business (Hal Investments, GrandVision) [13], [23] using different pricing and different marketing.

	Strategy description	Advantages	Disadvantages	Example companies / products
High price	Setting a high price is accepted as long as the customer experiences a balance between price and perceived quality of the product.	- Margin. - High price results in “quality image”.	- Expensive image attached to products results in lower sales.	Ferrari, Mercedes-Benz
Low price	A low price is aiming to attract more (new) customers. The achieved (and/or growing) market share determines the success of the low price strategy.	- New customers (affordability) - Encourage clients to switch to cheap alternative.	- Low long term price expectation - Low price results in “cheap image”.	Aldi, LIDL
Market segmentation	Segmenting the market is a strategy of splitting up potential customers in groups. Each group/segment is charged a different price for a specific tailor made product. The success of segmentation depends on the willingness of these customers to pay more or less to purchase the item.	- Better price / value match in customer segments	- More expensive production process	Dell (tailor made computers), every car manufacturer offering options
Discount pricing	Discount pricing is offering a set of products for a reduced price during a limited period. The reduced margin should be compensated by an increase in sales during and after the discount period. Discounting is often combined with heavy marketing. Discount pricing has a set end date.	- Attract more clients	- Problems achieving higher overall margin because of too wide discount (on to many products)	H&M, HEMA, van Haren, Scapino
Price skimming	Price skimming is often applied at new innovative product launches. The first offer of the new product is at a high price. The price is lowered over time to encourage sales. Often combined (and timed) with the "product lifecycle" theory. Applicable for less price sensitive clients, for example because there is a product monopoly at the introduction because of disruptive product innovation.	- Useful to reimburse huge investments made for R&D	- High price can only exist for as long as customers retain less price sensitive (for example because of the launch of new innovative product)	Launch of new Samsung smartphone, launch of Athom Homey.
Penetration pricing	Penetration pricing aims to introduce a product at an initial price lower than the current market price with the objective to achieve a (higher) market share. The price should be low enough to break down customer habits. Price penetration can be temporary, also explained as "low price strategy" during a period of time.	- Break down customer buying habits - Discourage entry of competitors	- Needs a low cost structure (and pressure to push down costs) in the organisation to survive	JAAP.nl, Jumbo supermarket
Yield management (revenue management)	Yield management (also called: revenue management) aims to anticipate to customers' and competitors' behaviour in order to maximize revenue.	- Maximize revenue	- Heavy price fluctuation can make customers insecure about buying decisions.	KLM, Hoteling industry, perishable goods in supermarkets

Table 2 pricing strategies according to Dolgui and Proth [16]

4 Design of experiments

Having gone through the state of the literature , we can use the gaps in literature to execute some practical research in the form of experiments. The experiments are executed at the Licentie2GO web shop.

In this chapter, the open questions found in literature will be applied on the business we are working in. In that respect, we will know that the problems we are evaluating during our practical research are not problems that are available at Licentie2GO-only, but they are more general problems. In that respect, our answers found during the experiments can deliver a broader solution to businesses as well as that they will complement existing literature. The generalizability of this research is limited because the measurements are not yet validated in another business or validated in expert reviews. More about the generalizability and their limitations is explained section 8.1.

The previous literature chapter learned us about the state of literature on dynamic pricing, e-commerce, marketing- and business-strategies. In order to apply these theories on the business we are currently working in, we will step by step evaluate the important aspects of literature found. Aspects found in literature are applied on the business and are marked ***bold***.

From Licentie2GO, we learned that customers are ***price sensitive*** in choosing the provider for purchasing their items. In literature, we found several related papers on ***webrooming*** (physical stores losing customers to internet-sellers with lower prices) and price-sensitive customers using ***pricebots*** for comparing prices on the cheapest online seller.

We also learned from literature on ***dynamic pricing*** that a lower price in general should lead to an increased number of sales. When implementing dynamic pricing a clear distinction between ***strategic- and myopic customers*** should be made. Myopic customers are generally showing an immediate response to a decreased price. Strategic customers may forecast on additional price changes in the future.

In order to implement dynamic pricing at Licentie2GO, and aiming at the best results for myopic as well as for strategic customers, we need to redesign the advertising strategy. Advertising budgets need to have a higher efficiency generating more revenue from each euro spend on online advertising. In order to realise such an improvement, we need to start investigating the fit between our ***marketing model*** and our ***customer segments***. We need to know where customers find the offers by Licentie2GO in order to make ***better segmentation*** in referring platforms (and their potential customers).

According to Licentie2GO, most of the customers are attracted by using pricebots. Price-sensitive customers are found in pricebots using advertising and offering low prices. Therefore, experiments will start in measuring results from pricebot-advertising (see next chapter).

After the experiments we will know the amount of customers found per pricebot. Using that knowledge, this research can continue optimizing segmentation and matching prices to the customer segments found.

5 Case study: pricing experiments conducted at Licentie2GO

The website Licentie2GO.com was used to measure the impact of changes we made on pricebots. Multiple pricebots are used for this experiment. To give an overview of how such pricebots contribute to the revenue of webshops, some basic elements are described in this first section. The next sections will describe the experiments that are conducted in more detail.

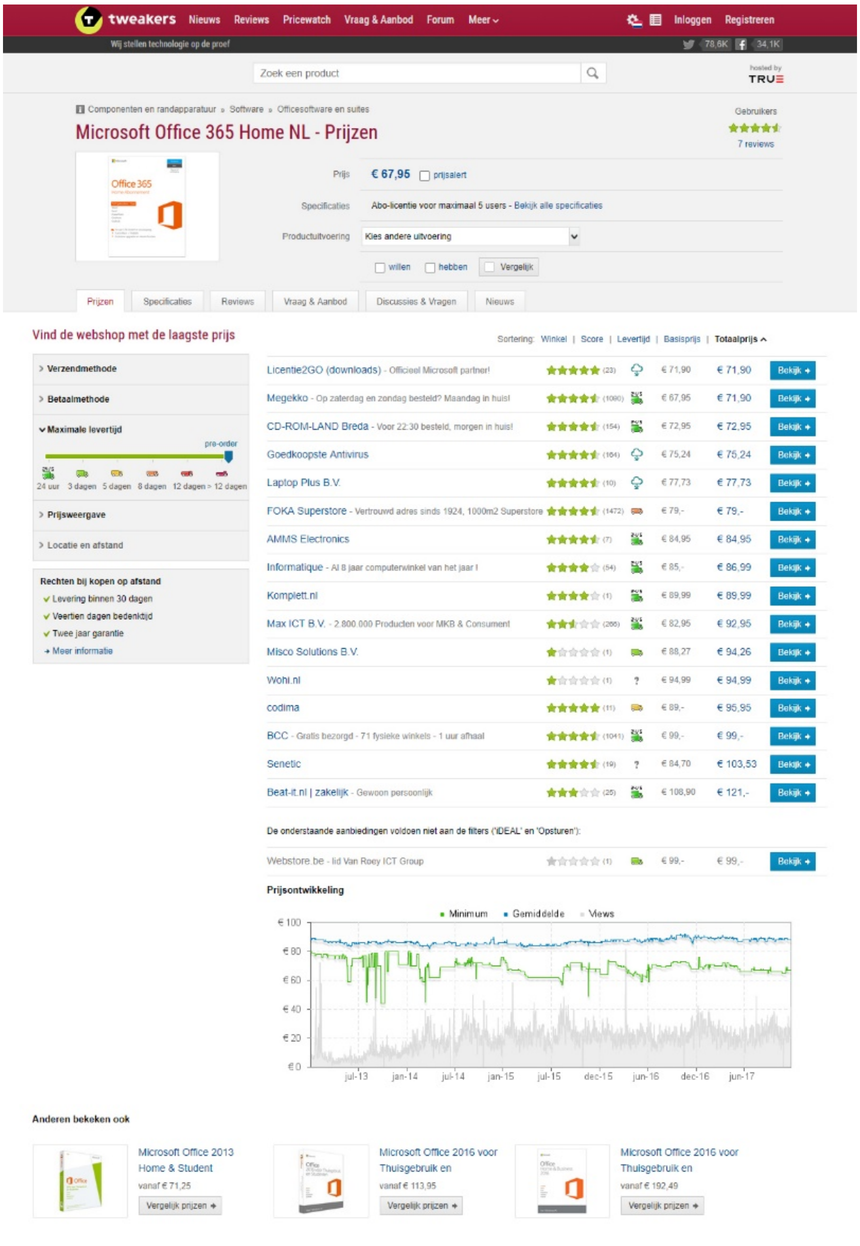


Figure 7 Example of a product (Office 365 Home) listed on a pricebot.

5.1 Pricebots explained

Pricebot is a term for a platform such as the Tweakers Pricewatch shown below. Pricebots collect data from webshops and the products sold by webshops. The data shown on the pricebot is delivered in an (XML-)feed from the webshop to the pricebot. Most of the time pricebots process these XML feeds about 12 times a day. An example of a product listed in the Tweakers Pricewatch pricebot is shown in Figure 7. The listing shows that a number of variables other than just the product name and the price are involved when a consumer needs to decide on the provider to deliver the product from this listing.

Variables other than sales price shown on the pricebot (or on the website Licentie2GO.com) are shown in Table 3. All of those variables might influence the outcome(s) of the experiment(s) so we'll make sure the variables are measured and are kept equal as much as possible. If we are not able to influence the variables (i.e. our user review or the average price) the variables will be measures continuously by a 3 times-per day page request on the pricebot (results are saved and compared to previous page request).

Other variables available on the pricebot platforms we use for our experiments are shown in the table below.

Table 3. Variables involved in reference price experiment

Variable	Location *(i.e. at the pricebot or Licentie2GO.com)*	Measured at competing shops?	Explanation
Promotional line	Pricebot	Yes	Promotional line of Licentie2GO is removed during the experiments.
Delivery time	Pricebot + Licentie2GO.com	Yes	The experiments will be executed with products that have real-time delivery. Competitors should have real-time delivery as much as possible to have a fair experiment.
Review-rating	Pricebot	Yes	Review rating will be measured during the experiment to measure the changes and their impact.
Additional costs *i.e. shipping-, payment-costs etc.*	Pricebot	Yes *(as long as they are shown in pricebot)*	No additional costs will be charged to consumers on the products in this experiment. No shipping costs, no payment costs, no other costs.
Payment methods	Pricebot	Yes *(as long as they are shown in pricebot)*	We will experiment with products in the Dutch market. Experiments will be done against other Dutch competitors. Most of them use iDeal and creditcard. Some also have Paypal and Afterpay.
Shipping methods	Pricebot	No	Shipping products to the consumer is out of scope for this research. When a consumer wants a physical shipment, Licentie2GO is not shown in the pricebot.
Average price	Pricebot	Yes, when available *(manually once a week)*	Only available on Tweakers. We will measure manually to measure the impact of average price of the product during the lifetime on customers buying decision.
Lowest price during lifetime	Pricebot	Yes, when available *(manually once a week)*	Only available on Tweakers. We will subtract the lowest price (lowest price ever) from the graph. Consumers may assume the price will decrease to this low-price level once again and wait for it.
Highest price during lifetime	Pricebot	Yes, when available *(manually once a week)*	Only available on Tweakers. We will subtract the highest price (highest price ever) from the graph. Consumers may assume the price will decrease if the price is near the highest price in the graph.

5.1.1 Relationships between variables

To conduct an experiment while changing 1 variable at the same time, we'll visualise the relationship between the variables below. Changing 1 variable may have an effect on other variables, so it is highly important to know the relationship between variables and how they influence each other.

The relationship in the variables is based on common sense, but also some other researchers wrote about these relationships. The authors are quoted in the relationship between variables as long as they are incorporated in our literature search. Because a lack of time, not all relationships are quoted from literature.

Pricing variables and their influence on sales.				
Lower price	→	if (price < reference price)	→	more sales
Lower price	→		→	more sales
Higher price	→	if(price > reference price)	→	reduced sales
Higher price	→		→	reduced sales
Price < average price	→	customers experience lower reference price	→	more sales
Price > average price	→	reference price < current price	→	reduced sales
Delivery variables and their influence on sales.				
Slower delivery	→	smaller customer base	→	reduced sales
Faster delivery	→	larger customer base	→	more sales
Higher review rating	→	Increased trust	→	more sales
Lower review rating	→	decreased trust	→	reduced sales
Payment and checkout variables and their influence on sales.				
Charging additional costs in checkout	→	customers leave checkout	→	reduced sales
No additional costs During checkout	→	customers complete checkout	→	more sales
Missing or incorrect Payment methods	→	decreased trust / convenience	→	reduced sales
Offer wide range of Payment methods	→	increased trust	→	more sales
Marketing variables and the influence on sales.				
Promotional line	→	increased trust → more clicks	→	more sales
Delivery variables and their influence on sales.				
Faster delivery	→	increased number of potential customers	→	more sales

5.1.2 Assumptions and preconditions for the experiments we are conducting in the next sections

Some basic assumptions need to be made and preconditions need to be set in order to successfully conduct experiments. They are required in order to gather data the right way and to make sure that data is reliable.

Preconditions are:

1. Multiple businesses offer the same product: Licentie2GO does not have a monopoly on products used in this experiment and there should be (healthy) competition among sellers;
2. Clicks from the pricebot to Licentie2GO are measured; other clicks (clicks from the pricebot to other sellers) cannot be measured;
3. Prices, delivery times, additional costs, review rating and the promotion line of competitors are measured continuously during the experiment;
4. The average price, lowest price and highest price of the product during the last year are measured during the experiment from the graph which is available on pricebot Tweakers.net;

Assumptions we've made are:

1. IP addresses are static during the visit. When a visitor comes back to the website after a while and is buying the product which he didn't bought at the first visit, we only use the data in the experiments as long as the IP address is the same as at his first visit.
2. The IP address for checkout (payment) is equal to the IP address used for visiting the website. If a visitor used a safe banking VPN, or the Tor network to be untraceable during the payment, the transaction is not recorded in our experiment.
3. The price shown in the pricebot is equal to the price which is charged during checkout on the Licentie2GO-website. We assume that all other sellers also charge exactly the price as mentioned on the pricebot to all of their customers. If other sellers give users a discount during checkout, they should have mentioned the lower price on the pricebot-platform (according to the terms they agreed in working with the pricebots).
4. All pricebots used have equal prices from our shop. For example; the price for Products A on Pricebot X is equal to the price for this product on Pricebot Y.

5.1.3 Pricebots and measurement-segments used in our experiments

In our experiments we used the 4 largest Dutch pricebots for comparing consumer electronics. According to Ecommercenews [66] those are:

1. Vergelijk.nl
2. Kieskeurig.nl
3. Tweakers
4. Google shopping

Since we could not use google shopping because Google Shopping does not allow software subscriptions to be compared in the Netherlands, we chose to replace Google Shopping with Hardware.info.

5.3 Experiment 1: Clicks & Sales from pricebots and the effect of price.

5.3.1 Goals

By executing this experiment, we'll try to accomplish 3 main goals:

1. *By combining the data sources that already are available, we will be able to measure the average number of clicks required to generate one sale.* [1]
2. *We will evaluate the reliability of our data by comparing multiple pricebot platforms against each other.*
3. *We can measure the increase/decrease of the number of clicks in case a product is advertised as "cheapeast", "second cheapest", "third cheapest" or more expensive positions in the pricebot.*

[1] This average number of clicks required for 1 sale is called: conversion rate. Conversion rate is calculated by "number of sales" / "number of clicks". I.e. when we received 100 clicks resulting in 3 sales, the conversion rate is 3%.

In this experiment we only focus on gaining new customers. Customers renewing their subscription or buying additional products are out of scope for this experiment.

5.3.2 Short description

We will request clickdata from pricebots to save that information in our own databases. This information is 100% reliable because it is real-time, raw data from the pricebot themselves. Every click linked to our pricebot is what the Licentie2GO has paid for.

The clickdata from pricebots platforms is matched with information we already have from visitors, like clicks on our website (the clickflow from first entry to completed sale), IP addresses from visitors and purchases they've made.

By combining this data from pricebots with our own data, we can calculate the number of sales coming from the pricebot platform. In addition, we can measure the impact of price changes on the number of clicks from the pricebot to our website.

5.3.3 Hypothesis

For the execution of this experiment, we expect that price alone is not a factor that is increasing / decreasing the number of sales from the pricebot. The position on the pricebot (i.e. cheapest seller / second-cheapest seller) is decisive for increasing/decreasing the number of sales.

H1. *Position 1 in the pricebot[2] (cheapest overall offer) is generating most sales compared to lower positions in a pricebot.*

We expect the first position to be most interesting because a top-position generates most clicks. When the website (landing page) looks reliable and the product is matching the advertisement, the customer should probably complete the sale at the cheapest offer.

In addition; customers using a pricebot are price-sensitive customers. They use the pricebot explicitly to find the cheapest offer. When the cheapest offer looks reliable, customers might compare a number of more expensive providers, but they are likely to compete their purchase. The #1 provider should do everything to look as reliable as possible because it is likely that this provider has the smallest margins.

H2. *Only when position 2 in the pricebot[2] has a small price-difference (< 0,50 EUR to position 1), position 2 is generating an equal number of sales compared to position 1.*

Providers in a pricebot should do everything they can in order to make their website look as reliable as possible. Assuming the #1 and #2 provider in a pricebot have a website that is looking equally reliable (we are not measuring nor defining reliability), customers might accept a small price difference as a certainty that they have made a reliable purchase.

We expect most customers to compare the top 3-5 providers in a pricebot in order to look for a cheap and reliable purchase. When comparing providers on equal price levels, we expect the providers to have an equal chance of achieving the sale.

H3. *Position 2 in the pricebot[2] with a high price-difference (> 0,50 EUR) will result in almost no sales compared to position 2 with a small price-difference.*

When customer compare prices, they'll look for a cheap and reliable offer. Licentie2GO is selling products with an average value per order around 45 EUR. We expect a price difference over 1% to be enough to push customers to buy at the cheaper provider in position #1. In this perspective we assume both providers (position #1 and #2) to have a website that looks equally reliable.

H4. The conversion on pricebot[2] A is considered to be comparable to the conversion on pricebot B when an equal price-level[3] is set on the platforms.

When executing experiments among multiple pricebots, we assume all visitors of those pricebots to have an equal "willingness to pay". They have chosen the product they want to buy, they don't compare alternatives and are just looking for the best provider to buy. Multiple providers offer the same product. In that perspective, we assume pricebots to have an equal conversion rate; an equal number of sales per 100 clicks. Precondition for this effect to happen is that the price-level is also equal among pricebots.

[2] In our current experiments we compared the 4 largest Dutch pricebots used for consumer electronics in which we measured software sales. For a more general overview of pricing in pricebots, one may repeat the experiments on other pricebots.

[3] An equal price level is set when the product measured on pricebot A is advertised on the same price and the same position (i.e. second-cheapest) as on pricebot B.

5.3.4 Workflow of the experiment (long description)

For this experiment we don't modify anything on the website, we'll just use the measurements that already are present (build into the website) and supplement our own data with an additional data source provided by the pricebot. Pricebots generally provide an exact dump of the click data of paid clicks they referred to our website. By combining these data sources, we present ourselves with new information.

Figure 8. Schematic overview [1,2] of experiment 1

[1] Please note that there is no link between visitors and orders. In addition; no link between orders and the referring platform cannot be established because we consider the average numbers from our databases.

[2] Please note that for each pricebot measurements should be gathered. Measurements are only available for pricebots that deliver the data sources (dump for clicks referred in a period of time). In the example, we used Tweakers Pricebot for clarification.

An example-response from the Tweakers data is shown below in Figure 9. In the response the clicks per day are requested. Not only the number of clicks are available, but also the (total) costs of these clicks based on the CPC payment method.

By combining the data exports from the pricebot and the analytics gathered from the website, we could combine the data in order to get new information. An example of the data from both data sources is shown below.

Table 4.Overview of clickdata provided by pricebots

Date_added	Product_ID	Platform_name	Visitor_IP
Exact DateTime (incl. sec) of the click	Product viewed	Referring platform (i.e. Tweakers Pricewatch)	(optional) not always supplied by Pricebot.
2017-10-01 10:04:01	1953 (Office 365 Personal)	Tweakers Pricewatch	n/a
2017-10-01 10:06:05	1975 (Norton Sec. Deluxe)	Tweakers Pricewatch	n/a
2017-10-01 10:06:05	1963 (Office 365 Home)	Kieskeurig	84.245.13.4

An internal database for measuring clicks on the website was already present. This database can be matched based on the IP address from the customer (if available) and/or based on the exact data and time that was clicked on the referral-link to a specific product from the pricebot. The only restriction is that when we don't know the IP address we can only match 1 visitor per second per product.

Table 5. Overview of internal database with clickdata

Date_added	Product_ID	Customer_ID	Visitor_IP	Referrer
Exact DateTime (incl. sec) of the click	Product viewed	(optional) only when customer logged in	IP address the visitor is using on our website	(optional) only available on first click.
2017-10-01 10:04:01	1953 (Office 365 Personal)	99485	37.97.216.143	n/a
2017-10-01 10:06:05	1975 (Norton Sec. Deluxe)	67458	66.249.64.28	http://www.tweakers.net/aclk?sa=l&ai=C-2ZcFr_FVt6AJOfTzAbOx4L4CeiD
2017-10-01 10:06:05	1963 (Office 365 Home)	n/a	84.245.13.4	n/a

```json
{
    "shopId": "99999",
    "shopName": "Licentie2GO",
    "filters": {
        "year": 2017,
        "month": 3,
        "day": 1,
        "skus": [],
        "eans": [],
        "productIds": []
    },
    "data": [
        {
            "date": "2017-03-01",
            "categoryId": "534",
            "priceRange": "0",
            "deliveryCountry": "NL",
            "productId": "102557",
            "productName": "Microsoft Office 365 Home NL",
            "categoryName": "Officesoftware en suites",
            "clicks": "4",
            "eans": [
                "0702168963592",
                "0763250859766"
            ],
            "skus":  "6GQ-00044",
            "costPerClick": "0.18",
            "cost": 0.72
        },
        {
            "date": "2017-03-01",
            "categoryId": "545",
            "priceRange": "0",
            "deliveryCountry": "NL",
            "productId": "284658",
            "productName": "Symantec Norton Security Deluxe 3.0 NL (1 jaar / 5 apparaten)",
            "categoryName": "Beveiliging en antivirus",
            "clicks": "2",
            "eans": [
                "0702168966470",
                "5397039337708"
            ],
            "skus": [
                "SYM-21355384"
            ],
            "costPerClick": "0.18",
            "cost": 0.36
        },

        ...

    ]
}
```


Figure 9. Response from the Tweakers API data-dump with clicks.

5.3.5 Measurements

Data is gathered by performing 8 different measurements. The 8 types we are measuring are described below. The images are for illustrative purposes only in the first 4 measurements we assume customers only look at position 1 and position 2 when they offer the same product at an equal (or almost equal) price. We compare our own platform with another comparable platform which has a comparable review-rating, delivery time and comparable additional costs during checkout.

For the easy of measuring we decided to use the largest pricebot in the Netherlands to conduct our experiments. Before drawing any conclusions, the data will be validated among the average results from other pricebots.

1. *First measurement, testing **H1**: Testing position 1 with equal price.* ***Measure Office 365 Personal on Tweakers.***
    a. Offer a product at a price X which is the cheapest offer. Equally to another competitor.

Licentie2GO (downloads) - Norton Gold partner!	★★★★★ (12)	€ 28,20	€ 28,20	Bekijk
Goedkoopste Antivirus	★★★★½ (128)	€ 28,20	€ 28,20	Bekijk

    b. Measure the number of clicks from this pricebot to our website.
    c. Measure the number of sales generated from these clicks on our website
    d. Calculate the conversion by: number of clicks / Number of sales.
2. *Second measurement, testing **H1**, **H2**: Testing position 2 with equal price.* ***Cannot be tested because of our all-time high review-rating.***
    a. Lower the review-rating to switch position in order to generate a fair base-measurement. Most likely we need to test this on another product than the product used in experiment 1.

Goedkoopste Antivirus	★★★★★ (12)	€ 28,20	€ 28,20	Bekijk
Licentie2GO (downloads)- Norton Gold partner!	★★★★½ (128)	€ 28,20	€ 28,20	Bekijk

    b. Measure the number of clicks from this pricebot to our website.
    c. Measure the number of sales generated from these clicks on our website
    d. Calculate the conversion by: number of clicks / Number of sales.
3. *Third measurement, testing **H1**: Testing position 1 with price-gap. Licentie2GO is 1 EUR cheaper than the offer on position 2.* ***Measure Office 365 Personal on Tweakers.***
    a. Decrease the price further, to generate a gap between the cheapest and second-cheapest offer.

Licentie2GO (downloads) - Norton Gold partner!	★★★★★ (12)	€ 28,20	€ 27,20	Bekijk
Goedkoopste Antivirus	★★★★½ (128)	€ 28,20	€ 28,20	Bekijk

    b. Measure the number of clicks from this pricebot to our website.
    c. Measure the number of sales generated from these clicks on our website
    d. Calculate the conversion by: number of clicks / Number of sales.
4. *Fourth measurement, testing **H2**, **H3**: Testing position 2 with price-gap to position 1. Licentie2GO is 1 EUR more expensive than the cheapest offer.* ***Measure Office 365 Personal on Tweakers.***
    a. Increase the gap to generate a position 2: only 1 offer is cheaper than ours

Goedkoopste Antivirus	(12)		€ 28,20	€ 28,20	Bekijk
Licentie2GO (downloads)- Norton Gold partner!	(128)		€ 28,20	€ 29,20	Bekijk

b. Measure the number of clicks from this pricebot to our website.
c. Measure the number of sales generated from these clicks on our website
d. Calculate the conversion by: number of clicks / Number of sales.

With the above 4 experiments, we were able to gather basic data on the impact of our offer on the first and second position on a pricebot. The next experiments are including more data using intelligent positioning in order to measure the impact of a higher position with logical pricing compared to others webshops offering the same product.

5. *Fifth measurement, testing **H2, H3**: **alone on first place (1/2).** Testing position 2 with logical distance to position 3 leaving one competitor alone on position 1 with a distance. There should be a gap between position 1 and 2. For this measurement we use **Office 365 Home on Tweakers.** Do consumers find a price gap of 7+ EUR at the cheapest offer and the following 4 offers a dangerous purchase?*
   a. We are positioning our offer on position 2 with a price-distance equal to the difference in position 3 and position 4. The difference between “Nandu software” and “Megekko” is € 0,95. Licentie2GO should be positioned at 70,95 – 0,95 = 70,00 EUR.

Goedkoopste Antivirus	(129)		€ 67,32	€ 62,32	Bekijk
Licentie2GO (downloads) - Officieel Microsoft partner!	(12)		€ 70,75	€ 70,00	Bekijk
Nandu Software - Binnen 1 minuut veilig digitaal geleverd	(7)		€ 70,95	€ 70,95	Bekijk
Megekko - Op zaterdag en zondag besteld? Maandag in huis!	(956)	24/5	€ 67,95	€ 71,90	Bekijk
CD-ROM-LAND Breda - Voor 22:30 besteld, morgen in huis!	(95)	24/5	€ 72,95	€ 72,95	Bekijk

   b. Measure the number of clicks from this pricebot to our website.
   c. Measure the number of sales generated from these clicks on our website
   d. Calculate the conversion by: number of clicks / Number of sales
6. *Sixth measurement, testing **H1**: **alone on first place (2/2).** Testing position 1 with a gap to the next offers in the list. There should be a gap between position 1 and 2. For this measurement we use **Office 365 Home on Tweakers.** Do consumers find a price gap of 7+ EUR at the cheapest offer and the following 4 offers a dangerous purchase?*
   a. We are positioning our offer on position 1 with a price-distance equal to the gap that was found in experiment 5.

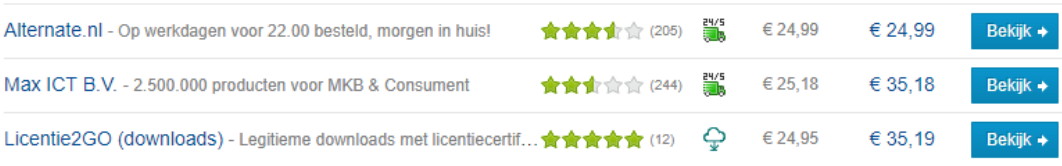
Licentie2GO (downloads) - Officieel Microsoft partner!	(15)		€ 63,07	63,07	Bekijk
Alternate.nl - Op werkdagen voor 22.00 besteld, morgen in huis!	(212)	24/5	€ 69,-	€ 70,75	Bekijk
Goedkoopste Antivirus	(136)		€ 68,31	€ 70,85	Bekijk
Nandu Software - Binnen 1 minuut veilig digitaal geleverd	(7)		€ 70,95	€ 70,95	Bekijk
Megekko - Op zaterdag en zondag besteld? Maandag in huis!	(977)	24/5	€ 67,95	€ 71,90	Bekijk
CD-ROM-LAND Breda - Voor 22:30 besteld, morgen in huis!	(106)	24/5	€ 72,95	€ 72,95	Bekijk

   b. Measure the number of clicks from this pricebot to our website.
   c. Measure the number of sales generated from these clicks on our website
   d. Calculate the conversion by: number of clicks / Number of sales

7. *OPTIONAL, testing **H2**, **H3**: Seventh measurement: measure the impact of user-reviews (2/3). Do customers choose our offer because our improved review-score?*
    a. Increase price to just over the amount of the lower-reviewed position 1 advertiser.

Alternate.nl - Op werkdagen voor 22.00 besteld, morgen in huis!	(205)	€ 24,99	€ 24,99	Bekijk
Licentie2GO (downloads) - Legitieme downloads met licentiecertif…	(12)	€ 24,95	€ 25,00	Bekijk
Max ICT B.V. - 2.500.000 producten voor MKB & Consument	(244)	€ 25,18	€ 35,18	Bekijk
Megekko - Op zaterdag en zondag besteld? Maandag in huis!	(956)	€ 33,95	€ 37,90	Bekijk

    b. Measure the number of clicks from this pricebot to our website.
    c. Measure the number of sales generated from these clicks on our website
    d. Calculate the conversion by: number of clicks / Number of sales
8. *OPTIONAL:* Ninth Measurement: *measure the impact of user-reviews (2/3). Do customers choose our offer because our improved review-score even if we are more expensive than 3 other advertisers?*
    a. Increase price to just over the amount of the lower-reviewed position 1 and position 2 advertiser.



Alternate.nl - Op werkdagen voor 22.00 besteld, morgen in huis!	(205)	€ 24,99	€ 24,99	Bekijk
Max ICT B.V. - 2.500.000 producten voor MKB & Consument	(244)	€ 25,18	€ 35,18	Bekijk
Licentie2GO (downloads) - Legitieme downloads met licentiecertif…	(12)	€ 24,95	€ 35,19	Bekijk

    b. Measure the number of clicks from this pricebot to our website.
    c. Measure the number of sales generated from these clicks on our website
    d. Calculate the conversion by: number of clicks / Number of sales

5.3.6 Outcomes of experiment #1

To start evaluating the outcomes of this first experiment, we analysed the data in order to question whether or not the data is suitable for accomplishing our experiment-goals.

Goal 1: *By combining the data sources that already are available, we will be able to measure the average number of clicks required to generate one sale.* [1]

ACHIEVED: From a pricebot perspective, this goal is achieved. The required data can be measured based on the current resources we have. We know the exact number of clicks from a pricebot because (except for 1 pricebot, Kieskeurig) all pricebots are supplying us with exact clickdata. In addition, we are able to measure the last-used pricebot using a tracking cookie. Using this data, we can calculate the number of sales per pricebot, the number of clicks and thus: the conversion. See Table 5 for the results of this experiment.

Table 6. Conversion rate pricebot experiment 1

#clicks	#orders	Conversion (%)	Originating pricebot
75	8	10,7%	Tweakers
26	6	23,1%	Kieskeurig
45	1	2,2%	Vergelijk Netherlands
2	0	0,0%	Vergelijk Belgium
1	0	0,0%	Hardware.info

Goal 2: *We will evaluate the reliability of our data by comparing multiple pricebot platforms against each other.*

FAILED: a big problem with this experiment is that the data appeared to be unreliable. To analyse the reliability of the data, we gathered and compared data from all pricebots that are doing business with Licentie2GO and analysed the differences. The pricebots that could supply API/CSV or XML data are:

1. Tweakers
2. Vergelijk
3. Hardware.info

Kieskeurig could not supply clickdata, but we managed to include the clicks from our own systems. When measuring the conversion rate (#orders / #clicks) we expected to be the conversion rate to be equal among all pricebots. However, the numbers appeared to be very different among the platforms. See Table 5 for the different results.

We analysed the clicks on originating IP addresses and on browser-tags to find out an explanation for the differences. It appeared that a very large amount of the clicks from Vergelijk are from crawlers (2.2% crawlers). They are for example the Google Search engine index Robot and the index robot for Microsoft Bing Search. The low conversion rate of 2% appeared to be no error in the measurement but explainable because the clicks are not from real visitors but from robots.

In addition; the 10% conversion from Tweakers appeared to be realistic. Consumers on Tweakers are very price-sensitive and the competition is fierce. Not all suppliers on Tweakers also advertise their products on Kieskeurig. However, we used internal analytics to calculate the conversion rate on Kieskeurig, 23,1% appeared to be very high. On Kieskeurig a lot less advertisers for software are available, but 23% conversion seems a bit high. We really question the reliability of the data here, so that should be improved by executing a next experiment.

Goal 3: *We can measure the increase/decrease of the number of clicks in case a product is advertised as "cheapeast", "second cheapest", "third cheapest" or more expensive positions in the pricebot.*

FAILED: To analyse increases or decreases in the number of sales based on the position in pricebot, we need to know position in the pricebot as well as the number of sales realised on that position. For a detailed analysis on this point, we set-up an experiment using hypothesis **H1**-**H4**.

H1 **cannot be answered based on the current data.** Experiment appears to be suitable to test this hypothesis, but we need more data and better measurements about the current position in the pricebot on a chosen timeframe (timeframe of experiment execution). Biggest problem in this experiment is the "race-to-the-bottom"; once we change our price, competitors automatically decrease their price in order to be even cheaper as our cheapest offer.

H2 **cannot be answered based on the current data.** Experiment appears to be suitable, but we need more data and better measurements about the current position in the pricebot on a chosen timeframe (timeframe of experiment execution). Biggest problem in this experiment is the price-difference we choose. 0,50 might be reasonable, but it might also affect the seller on position 3. In addition; an exact difference is hard to maintain. It needs a lot of effort and measurements to keep the data clean and reliable.

H3 **cannot be answered based on the current data.** The data appeared to be unreliable. In addition; we need more data to draw conclusions on this hypothesis. Sufficient products in our assortment could be found to be placed on a position 2 with a large price difference. However, the problem is that those products are most of the time unpopular products having insufficient traffic to supply us with enough data to draw any conclusions.

H4 **cannot be answered based on the current data.** The data appeared to be unreliable. In addition; we need more data to draw conclusions on this hypothesis. Based on the current situation one might assume that conversion among pricebots can be different based on the popularity of products and the level of competition. However, because the data is not reliable enough, we cannot draw this conclusion yet.

5.3.7 Optimizations for next experiment

From this experiment we learned that we should make sure that there is sufficient data to draw conclusions from. The data from the Tweakers pricebot was not enough to draw conclusions from. We need more data from other pricebots to draw conclusions.

For the next experiment we are grouping products in categories with similar characteristics. We try to repeat the experiment with the product groups to gather enough data to draw conclusions.

The race to the bottom should stop in order to gather enough data. If we continue fighting for position 1 in the pricebot we not only risk the reliability of our data but we also diminish our margins. To solve this issue, we will conduct experiments on groups of products by placing all products in the group on the same conditions. For example; the Norton Security product groups exists of 4 products:

1. Norton Security Standard – 1 device
2. Norton Security Deluxe – 3 devices
3. Norton Security Deluxe – 5 devices
4. Norton Security Premium – 10 devices

The product is equal, the product configuration (on how many devices can you install?) is different. Therefore, we expect the “willingness to pay” for all products in the group to be equal making this product group suitable to be used in our experiment.

For the next experiment we will make product groups. Each product group is placed on a certain position in a certain pricebot. This will speed up the measurements by gathering because we gather data much faster than using 1 product on 1 pricebot for 1 experiment. By repeating the experiment on multiple pricebots we can easily validate the reliability of the data.

5.4 Experiment 2: First wall of entry for pricebot visitors

5.4.1 Goals

By executing this experiment, we are gathering reliable data to analyse the positions and conversion on the pricebot platforms. In order to measure enough data, we group products to execute our measurements on product groups instead of on individual products.

1. Gather reliable clickdata from pricebots to match that data with our internal systems for analytics.
2. Measure the conversion for product groups advertised on a chosen position in the pricebot (i.e. cheapest or second-cheapest offer) [2].

[2] All products in the group are carefully chosen based on mutual product characteristics such as brand, product range, product lifetime etc. All products in the product-group are advertised on the chosen position (i.e. #1 position for the cheapest offer or #2 position for second-cheapest offer).

5.4.2 Short description

To gather data that is 100% reliable for matching in our analytics, we won't use API/CSV-data from pricebots anymore. The data they provided appeared to be unreliable because of bots clicking on the paid links.

We redirected all visitors from pricebot platforms to our portal, also called "wall of entry". After landing on the wall of entry, we gathered our own data such as "unique click ID", "IP address", "product clicked", "price communicated on the pricebot" etc.

We matched the (more reliable) data from our wall of entry with our own systems to calculate conversion, to measure the impact of price changes and to measure the flow of visitors from pricebot to completed purchase.

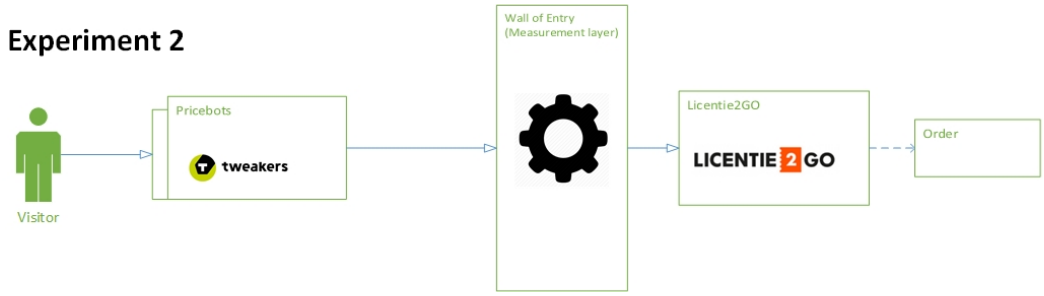


Figure 10. Schematic overview [1,2,3] of Experiment 2

[1] Please note that there is no link between visitors and orders. In addition; no link between orders and the referring platform cannot be established because we consider the average numbers from our databases.

[2] Please note that using this new technology no data from pricebots is needed anymore. Every click at a pricebot is recorded in our "Wall of Entry".

[3] When a visitor is using multiple pricebots, we can now detect all clicks from all pricebots combined and link the clicks back to one visitor based on session data, IP-address and technical recognition of the browser.

The source code of our "Wall of Entry" (to explain the technical working of our system) is classified and therefore not published. However, to prove the technical working, the description can be found in the appendix together with parts of the source code.

5.4.3 Hypothesis

For the execution of this experiment, we tried to find out a reliable answer on the hypotheses **H1-H4** from experiment 1. In addition, new hypotheses were added:

H5. *The wall of entry is able to detect mismatches between the price of a product on the pricebot and the actual data on the website.*

Detecting a mismatch between information presented on the pricebot and information presented on the website is very important because customers' expectations are not fulfilled. In other words, a mismatch in information is also a mismatch in expectations.

Mismatches can be detected by letting the pricebot send the information they presented on their platform along with the referral request for the customer. The information is send in variables in the website URL referring the customer from pricebot to our website. In this respect, the tool should be able to detect mismatches because we already know there is a delay in information processing on the pricebot platforms.

H6a. *A mismatch between data on the pricebot and data on the website which is negative for the consumer (price on the website is higher than shown on the pricebot) is killing the sale: all visitors will bounce when a price-mismatch negative for the consumer is present.*

As explained before; a mismatch in information is also a mismatch in expectations. When expectations are not matched, we expect customers to bounce. They lose trust when promises on the pricebot appear to be not realised on the website. Especially when the information shown on the website is a negative surprise for the customer, the customer doesn't trust the website anymore and is buying elsewhere.

H6b. *A mismatch between data on the pricebot and data on the website which is positive for the consumer (price on the website is lower than shown on the pricebot) is lowering conversion.*

Even if the information presented on the website (different than shown on the pricebot) is in favour of the customer, we expect customers to bounce and to buy elsewhere. We expect them to loose trust and therefore buy on another website that is matching the pricebots information. If there is sufficient data we might see that a number of customers is buying at our website is buying the product (hoping that the better information is true), but the conversion rate will be lower than average because of lowered trust.

H7. *Using our wall of entry, we can measure the number of clicks from robots and search engines on paid clicks from pricebots when we combine that traffic with internal databases already present within the organisation*.

Our wall of entry is measuring all IP addresses and variables from the users' web browser. According to these values, we should be able to detect (search engine) robots. The importance of automatically clicking robots was already shown in the previous experiment. Because of robots clicking the links, the conversion rate is lowered making it less profitable to advertise on such pricebots.

H8. *Using our wall of entry, we can measure the number of pricebots used by visitors to compare the product before making the actual purchase.*

Because we are tracking all visitors and their clicks, the wall of entry should be able to detect recurring visitors. Recurring visitors using multiple pricebots are extremely price sensitive customers comparing prices on multiple pricebot-locations. If a pattern can be found on multiple pricebots being used by large groups of customers, it could be interesting to just quit cooperating with those pricebots because in such a situation the additional pricebot doesn't contribute to generating more (new) customers or website visitors.

[3] An equal price level is set when the product measured on pricebot A is advertised on the same price and the same position (i.e. second-cheapest) as on pricebot B.

5.4.4 Workflow of the experiment (long description)

For this experiment, the flow of visitors from pricebot-platforms to the Licentie2GO-website is modified. The most important benefits from this modification are the reliability of the data. Experiment 1 had major problems with data reliability and the absence of data needed for reliable analysis.

To mitigate the reliability- and completion-issues of the measurements, we've build and implemented a new tool on our website to solve this issue. The tool is focussed on pricebot-platforms, because they are the most important tools to measure the impact of price-changes.

Using this visitor-recognition-tool, we not only gathered more data, we also gathered more reliable data. The visitor-recognition tool is able to:

1. Detect visitors from all pricebot platforms that are connected to our XML feeds (we focus on the 4 largest pricebot-tools for consumer electronics in the Netherlands);
2. Detect the price shown on the pricebot platform;
3. Detect a price mismatch between the information present on the pricebot and the Licentie2GO-website;
4. Detect whether the click on the advertisement was realised by a customer or a (Search Engine) Robot;
5. Detect when a visitor uses multiple pricebots to compare our products on 2 or more pricebot-platforms.

The modifications impacted the flow of visitors from pricebot to the Licentie2GO website. First, the pricebot-platforms are given other URLs that link to the Licentie2GO website. The URLs are changed from pointing directly to the product, to pointing to a welcome page, see Figure 11.

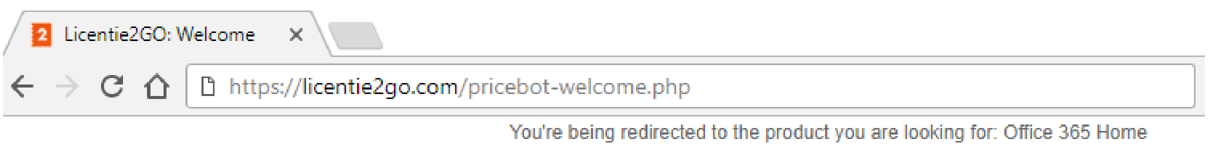


Figure 11. Visitors being redirected from pricebot to product.

5.4.5 Data gathered & visitor identification

In just a split-second this single welcome-page is gathering important data from the visitor such as:

1. IP address
2. Cookies from previous visit
3. Setting a new cookie to detect future-visits. Cookie lifetime is set on the max. value.
4. The price which was shown on the platform itself (based on a variable in the URL)
5. The customers' session is recorded with a local storage object in the browser (client side). This local object doesn't have a lifetime, so it will exist for ever in the browser. When cookies are expired, the local object will continue to exist.

In addition to recognising visitors on their next visit, we also stored information we presented to the customer during each visit. In our database, the visitor is given a unique ID. Based on this ID, we could offer the recurring visitor the same information (or changed information) based on the experiment we are executing.

The visitor ID is stored in the cookie and in the local storage object, present on the visitors device used to visit our website.

Table 7 Structured data gathered in databases in Experiment 2

Date_added	Visitor_ID	Product_ID	Price	P_Price	Visitor_IP	Referrer	C_costs
Exact DateTime (incl. sec) of the click	The unique ID assigned to the visitor	Product viewed (the target page of the visitor)	The price(EUR) of the product shown at Licentie2GO	The price (EUR) of this product shown on the pricebot	IP address the visitor is using on our website	Based on the platform (referrer) used.	The actual costs (EUR) of each visitor referred
2017-10-01 10:04:01	1	1953 (Office 365 Personal)	37,15	37,15	37.97.216.143	Kieskeurig	0,30
2017-10-01 10:06:05	2	1975 (Norton Sec. Deluxe)	25,58	25,60	66.249.64.28	Tweakers	0,45
2017-10-01 10:06:05	3	1963 (Office 365 Home)	60,24	60,24	84.245.13.4	Tweakers	0,45

5.4.6 Measurements

The measurements performed are similar compared to the previous experiment. Again, we performed the measurements based on the Tweakers Pricewatch.

The situations that are measured in this experiment are equal to those in experiment 1. However, they are slightly adjusted to make them work because we already learned that some desired situations could not be executed.

In addition; when comparing and analysing results, we grouped some products in order to have more data available. For example; Office 365 Personal and Office 365 Home are comparable products. When they are at the same position in the pricebot, we can group the results in order to analyse the data from 2 products at once.

All experiments below are able to test Hypothesis **H5**, **H7** and **H8**. If conditions are met also **H6a** and **H6b** could be tested.

1. *First measurement, testing **H1**: Testing position 1 with equal price. **Office 365 group: 365 Personal and 365 Home and Norton Security group.***
   a. Offer a product at a price X which is the cheapest offer. Equally to another competitor.

Licentie2GO (downloads) - Norton Gold partner!	(12)	€ 28,20	€ 28,20	Bekijk
Goedkoopste Antivirus	(128)	€ 28,20	€ 28,20	Bekijk

   b. Measure the number of clicks from this pricebot to our website.
   c. Measure the number of sales generated from these clicks on our website
   d. Calculate the conversion by: number of clicks / Number of sales.
2. *Second measurement, testing **H1**, **H2**: Testing position 2 with price-gap to position 1. Licentie2GO is 1 EUR more expensive than the cheapest offer. **Office 365 group: 365 Personal and 365 Home and Norton Security group.***
   a. Increase the gap to generate a position 2: only 1 offer is cheaper than ours

Goedkoopste Antivirus	(12)	€ 28,20	€ 28,20	Bekijk
Licentie2GO (downloads)- Norton Gold partner!	(128)	€ 28,20	€ 29,20	Bekijk

   b. Measure the number of clicks from this pricebot to our website.
   c. Measure the number of sales generated from these clicks on our website
   d. Calculate the conversion by: number of clicks / Number of sales.
3. *Third measurement, testing **H1**: position 2 with a price-gap. Tested on multiple security products (security-group) on the Tweakers Pricewatch.*
   a. We are positioning our offer on position 2 with a price-distance equal to the difference in position 3 and position 4. The difference between "Nandu software" and "Megekko" is € 0,95. Licentie2GO should be positioned at 70,95 – 0,95 = 70,00 EUR.

Goedkoopste Antivirus	(129)	€ 67,32	€ 62,32	Bekijk
Licentie2GO (downloads) - Officieel Microsoft partner!	(12)	€ 70,75	€ 70,00	Bekijk
Nandu Software - Binnen 1 minuut veilig digitaal geleverd	(7)	€ 70,95	€ 70,95	Bekijk
Megekko - Op zaterdag en zondag besteld? Maandag in huis!	(956)	€ 67,95	€ 71,90	Bekijk
CD-ROM-LAND Breda - Voor 22:30 besteld, morgen in huis!	(95)	€ 72,95	€ 72,95	Bekijk

   b. Measure the number of clicks from this pricebot to our website.
   c. Measure the number of sales generated from these clicks on our website

d. Calculate the conversion by: number of clicks / Number of sales

4. *Fourth measurement, testing **H1**: **alone on first place (2/2).** Tested on the Office 365 group and the Norton group on Vergelijk.nl. Multiple other sellers are on this pricebot with much higher pricing.*
    a. We are positioning our offer on position 1 with a price-distance equal to the gap that was found in experiment 5.

    b. Measure the number of clicks from this pricebot to our website.
    c. Measure the number of sales generated from these clicks on our website

5.4.7 Outcomes of experiment #2

To gather reliable clickdata, a wall of entry for pricebot visitors was implemented. A total of 21902 clicks were measured in the period of our experiment. However, only 2406 clicks could be assigned to a pricebot.

The clicks were measured from more pricebots than the bots used in experiment 1 (see the table below). We could match orders based on the last-used pricebot. For example; when a visitor uses 2 pricebots to compare prices (i.e. Tweakers and Kieskeurig), only the last used platform was recorded. The results are shown in Table 8 below.

Start of measurements: 06-09-2017
End of measurements: 31-10-2017

Table 8 Summary of results in Experiment 2

Platform	#CLICKS	#ORDERS	Conversion
Kieskeurig	205	25	12%
Tweakers	718	163	23%
Vergelijk NL	131	10	8%
HardwareInfo	25	2	8%
Vergelijk BE	7	2	29%
Daisycon	1	0	0%
Google Adwords	1319	62	5%
	2406	264	11%

The total black box of clicks needs to be analysed in more detail. Figure 12 gives an overview of the cleaning process of all data gathered. Because our tool logged all “headers” and “ip-addresses” we were able to detect normal visitors and bots clicking the paid traffic.

Unfortunately, after the cleaning process only 11% of traffic was remaining. A number of bots could be detected from the headers, but also based on reverse-ip-lookup we could identify a large number of "bots".

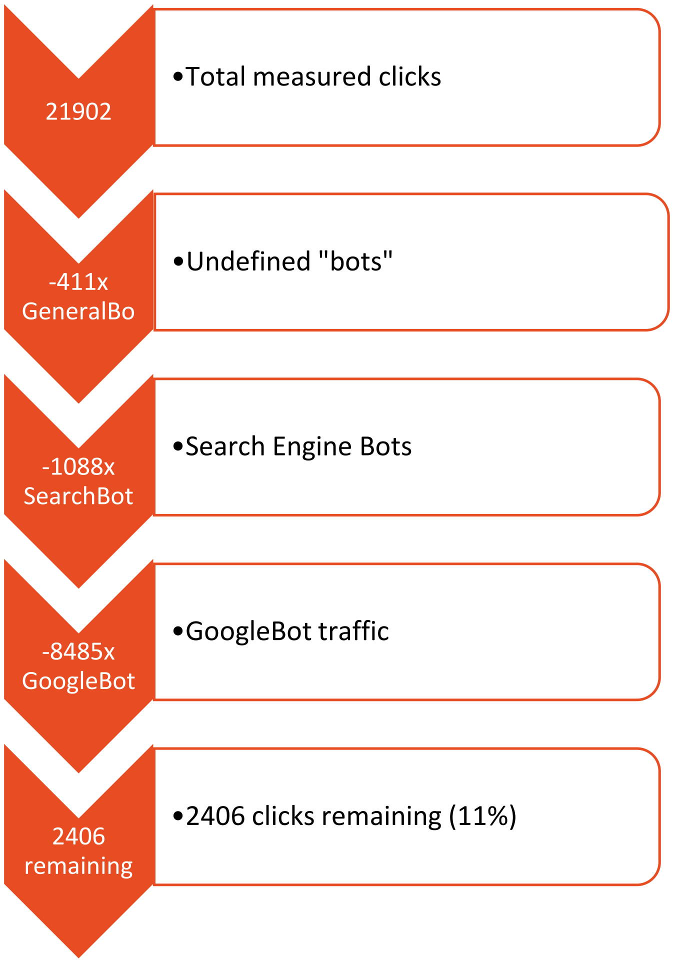


Figure 12 Cleaning process of clicks in Experiment 2

The fact that only 11% of clicked traffic could be assigned to a pricebot platform may have a number of reasons. One possibility is that pricebots are not fair in invoicing traffic to the business. Another explanation could be that a large number of bots is visiting the website to slow down the experience for "normal" customers or to steal information and content on the site. Slowing down the site is unlikely because a lot more traffic is needed to realise a slow-down of the site.

To make sure measurements are reliable, an extention to the measurement tool needs to be implemented. To really say something about the data, we not only need to have traffic from pricebots, but all other sources of traffic need to be implemented in the tool. For example, Google Adwords advertising, natural search results in Google and other search engines and the amount of renewal-traffic that is visiting the website based on renewal-mails we are sending to customers that need to renew their subscription.

5.4.8 Goals and hypothesis

Goal 1: *Gather reliable clickdata from pricebots to match that data with our internal systems for analytics.*

ACHIEVED: The data we gathered is reliable enough to be used for our measurement-goals. The variables that are important for influencing the outcomes of our experiments can all be measured. For example; price on our website, price shown in the pricebot, number of clicks from visitors, number of clicks from robots etc. With this tool, we are able to match all visitors based on a unique tracking system. We know their IP addresses, we know recurring visits etc.

Goal 2: *Measure the conversion for product groups advertised on a chosen position in the pricebot (i.e. cheapest or second-cheapest offer).*

POSSIBLE The measurement tool provides all resources needed to execute this measurement. However, most important for this goal is to know the position in the pricebot of certain products at a period in time. To execute this experiment and have 100% reliable conclusions, we need to buy data from pricebots (about positions and prices). Another solution is to measure prices of competitors in the pricebot with our own measurement tool. Our current tool does measure prices and positions, but because of detection in Tweakers, the tool was not reliable enough to conclude on a position at every measurement.

H1 *Position 1 in the pricebot[2] (cheapest overall offer) is generating most sales compared to lower positions in a pricebot.*

Insufficient data. The tools are in place, the measurements can be executed, however we have insufficient data to conclude on the best position in the pricebot. When executing this experiment over a longer period of time, we are able to gather enough data. However, the position in the pricebot cannot determined reliable enough to conclude anything about this.

H2 *Only when position 2 in the pricebot[2] has a small price-difference (< 0,50 EUR to position 1), position 2 is generating an equal number of sales compared to position 1.*

Insufficient data. The tools are in place, the measurements can be executed, however we have insufficient data to conclude on the best position in the pricebot. When executing this experiment over a longer period of time, we are able to gather enough data. However, the position in the pricebot cannot determined reliable enough to conclude anything about this.

H3 *Position 2 in the pricebot[2] with a high price-difference (> 0,50 EUR) will result in almost no sales compared to position 2 with a small price-difference.*

Insufficient data. The tools are in place, the measurements can be executed, however we have insufficient data to conclude on the best position in the pricebot. When executing this experiment over a longer period of time, we are able to gather enough data. However, the position in the pricebot cannot determined reliable enough to conclude anything about this.

H4 *The conversion on pricebot[2] A is considered to be comparable to the conversion on pricebot B when an equal price-level[3] is set on the platforms.*

Insufficient data. The tools are in place, the measurements can be executed, however we have insufficient data to conclude on the best position in the pricebot. When executing this experiment over a longer period of time, we are able to gather enough data to draw conclusions on this hypothesis. The measurements that are available now indicate that conversions vary a lot among different pricebot platforms. In the next experiment we will analyse data over a longer period of time in order to analyse more data.

H5. *The wall of entry is able to detect mismatches between the price of a product on the pricebot and the actual data on the website.*

TRUE. We succeeded in analysing the reliability of the data on pricebot platforms. Every link from a pricebot clicked to our website included the price which was shown on the pricebot. This price was matched against the price on our website. We learned that the speed of updating the price on several pricebot platforms varied among 1 run every hour (Tweakers) to 4 runs a day (Vergelijk).

H6a *A mismatch between data on the pricebot and data on the website which is negative for the consumer (price on the website is higher than shown on the pricebot) is killing the sale: all visitors will bounce when a price-mismatch negative for the consumer is present.*

Insufficient data. The tools are in place, the measurements can be executed, however we have insufficient data to conclude on the best position in the pricebot. When executing this experiment over a longer period of time, we are able to gather enough data to draw conclusions on this hypothesis

H6b. *A mismatch between data on the pricebot and data on the website which is positive for the consumer (price on the website is lower than shown on the pricebot) is lowering conversion.*

Insufficient data. The tools are in place, the measurements can be executed, however we have insufficient data to conclude on the best position in the pricebot. When executing this experiment over a longer period of time, we are able to gather enough data to draw conclusions on this hypothesis

H7. *Using our wall of entry, we can measure the number of clicks from robots and search engines on paid clicks from pricebots when we combine that traffic with internal databases already present within the organisation.*

TRUE. Our tool recorded not only the IP addresses that clicked on paid advertising in pricebots, but also the header for browser identification. The header is normally used to determine the version of the browser used to visit our website. I.e. Internet Explorer or Firefox. However, the honest bots crawling the Internet also identify themselves in the header. For example; Google and Bing are showing a header like:

Mozilla/5.0 (compatible; Googlebot/2.1; +http://www.google.com/bot.html)

Some bots are detected as dishonest bots. A few IP addresses seemed to browse our website without identifying themselves as a search engine bot. They might be bots build by competitors to index our website. Most of the time those bots are from large Internet Providers like Amazon, Leaseweb, Your-Server, Verizon, Savvis, OVH or others.

In addition; we matched the search engine headers with the IP addresses used. By combining those 2 identifiers we are absolutely sure to identify honest search engine bots at their next visit. Other dishonest bots are automatically blocked when they go over certain botdetection limits build into our website.

H8. *Using our wall of entry, we can measure the number of pricebots used by visitors to compare the product before making the actual purchase.*

TRUE. Our previous measurement used to place only 1 cookie on the device used by the visitor. That 1 cookie recorded the pricebot platform, but it was overwritten when a second pricebot platform was used. Therefore, we could only record the last-known pricebot platform. Using our new and improved measurement tool we recorded our unique visitors in our internal database. Each visit to our website made by this visitor was linked to a referring platform. Every pricebot used is in this respect mapped and visible in our database. Using this new technique, we are able to detect all pricebots the visitor used during the visits to our website.

5.4.9 Optimizations for next experiment

From this experiment we learned that we should make sure that there is sufficient data to draw conclusions from. In addition; besides having enough data measure on the products itself, we also need to have data supporting our conclusions. In this experiment, we need data about the position of our products in the pricebots. A reliable determination of the position in a pricebot seem to be hard. Not only because we would like to measure the position on every click (frequency of measurements), but also because our tool to measure positions was frequently discovered and blocked in the pricebots.

5.5 Experiment 3: Improved wall of entry for all visitors

5.5.1 Goals

For this last experiment, not only pricebots are considered in our measurements for referring traffic to the Licentie2GO-website, but also all other referring websites are mapped. With this mapping, we want to achieve a number of things:

1. Measure (and discover) traffic from all referring websites instead of just pricebots (that we already know).
2. Measure conversion from all referring websites;
3. Calculate the costs of paid clicks from referring websites;
4. Measure the minimum required margin per product (group) per referring website.

The ultimate goal of knowing the minimum required margin per product (or: group of products) per referring website is to optimize our sales price on such a platform. The sales price can be optimized to the optimum of achieving the highest margin, a maximum number of new clients or any other chosen strategy. Requirement for this is that we can forecast the results of changing the price. We might decrease the number of new customers from a certain platform, but when that doesn't affect other platforms, the margins might increase. More about those strategies and optimizations will be explained in the next sections.

5.5.2 Short description

The wall of entry (measurement-tool from our previous experiment) was modified in order to gather data from all referring websites. In the previous experiment, the tool was only able to measure visitors and their purchases entering our website via a pricebot tool. In this experiment, we measure all referring websites, without the need to setup or connect the referring websites to our measurement tool.

Almost all visitors should have a referring platform these days. That platform can be a mail client (visit our website because they received one of our mailings), can be a search engine (they Googled one of our products), a pricebot, or just an informative website about one of our products. The possibilities are endless. We use the server-side HTTP_REFERRER to pick up the referring platform.

The only visitors without a referring website are those that typed in our URL directly or those visitors that are blocking our measurement-tool for ultimate privacy (i.e. incognito-browsers). Analytics already indicate that only a very limited number of users is typing in our website directly in the address bar resulting in losing or not having the HTTP_REFERRER variable. We will never know how those users found our website, unless they already used a connected referral before and continue to make a purchase. If they used a known referral and they really make a purchase, we will recognise the referring websites afterwards because of our cookie recognition system in the checkout-complete page.

By gathering data from all referring websites (not only from pricebot-platforms), we are able to measure conversion from all referring websites (and the costs attached to these referring clicks). The costs are implemented in a measurement tool to calculate the minimum margin per sale per referring website.

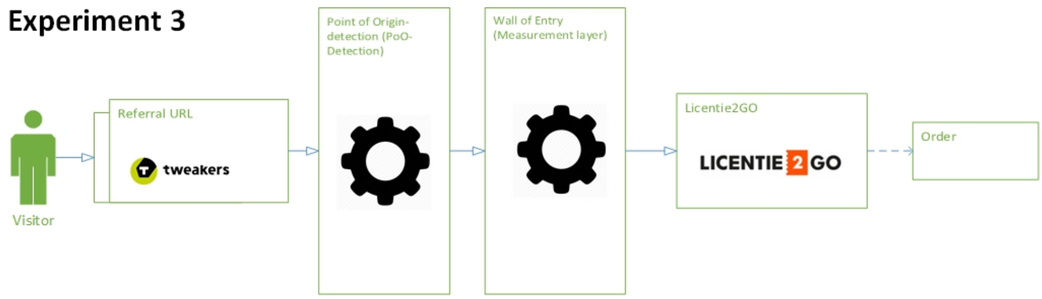


Figure 13. Schematic overview [1,2] of Experiment 3

[1] Please note that there is now a link established between visitor and order. An order can now be traced back to multiple clicks from all referring platforms.

[2] No interaction or set-up with external platforms is required anymore. If a link is clicked on any previous referral, our tool can detect the referring platform.

5.5.3 Hypotheses

While executing this experiment we were able to measure the hypothesis **H1-H8** again because our improved wall of entry is able to measure pricebot traffic AND all other referring websites. By doing so, we could approve the answers on **H1-H8** from the previous measurement again, just because in this experiment we can measure the same pricebot-traffic again. In addition, we expect the following things 3 hypotheses to happen using our improved "wall of entry"-measurement tool:

H9. *Using our improved wall of entry, we can identify sources of entry that visitors use to visit our website without having to setup those platforms using tracking cookies or any other manual action.*

By using the HTTP_REFERRER variable from the users browsing-session, we expect to identify all sources of entry that link to the Licentie2GO-website. All modern browsers should have such a HTTP_REFERRER variable. We expect most customers to find our website by advertisement-links placed on other websites with a large amount of traffic. In that perspective, this measurement should be able to help the organisation to identify all sources of traffic to the website.

H10. *Using our improved wall of entry, we can identify the total amount of clicks from robots (non-human internet traffic) from paid referrals to our website.*

Just like in the previous experiment, our improved tool still measures the IP addresses and the header for browser identification. In this perspective we do not only measure bots on pricebots referring traffic to the website, but we are able to identify all sources of paid traffic that is sending bot instead of human internet users to our website.

H11. *Using our improved wall of entry, we can calculate the minimum margin per product- or product group based on the conversion rate on the referring website.*

The improved wall of entry is able to identify all clicks and sales realised by referring platforms. Because of these statistics the tool should be able to calculate the average number of clicks needed to realise a sale. If we have these statistics per referring platform, per product (group), the minimum margin per product (group) can be calculated based on these advertisement costs.

5.5.4 Workflow of the experiment (long description)

The outcome of experiment 2, forced us to gather more data about where customers come from. How do they find our website if they are not from pricebot platforms?

For measuring all external visitors, we've improved the wall of entry measurement tool. For pricebot-platforms the tool is unchanged. They are all connected to our website via XML-files. Using this connection, we are set gathering all possible data.

However, for all other external platforms, we are unable to connect sites using XML or any other technology. The main reason for this is that any platform should be manually set up which is not desirable to do because we are likely to miss traffic. To solve this issue, we used the HTTP_REFERRER which is available in the session of the user when a link was clicked to refer to the Licentie2GO website. Still, for pricebot platforms the new tool used the XML connection if available. If not; the HTTP_REFERRER is used. HTTP_REFERRER is available on the first hit of our website and is stored rightaway. HTTP_REFERRER contains the URL of the referring website. However, it only contains this value when a link was clicked. An example;

1. The visitor is browsing the web on Google. Google links to our website (licentie2go.com/Norton-deluxe) in the search results. The visitor clicks the link. Our

tool will pick up the HTTP_REFERRER and our tool will know the exact page with the exact search on Google that the visitor was using.

2. However, when the visitor is using Google and decides to type in our URL in the address bar of his browser, the HTTP_REFERRER is empty. We will never know which sites were visited by the user before when a user types in the URL in the address bar directly because of improved privacy setting which are default in today's modern browsers.

All other options we tried to figure out which websites the user had visited before, failed. Previous researchers in literature suggested to use technologies to read the users browsing history, but unfortunately, users and browsers become more and more privacy-sensitive and all of those options are blocked today. The result of this is that all options to view URLs visited before are locked and cannot be seen anymore by other websites.

The results of our improved tool can give us great insights on the effect of showing the price of an online advertisement: Does an offer which is showing the (reduced) price lead to a greater increase in sales compared to an offer which is NOT showing the decreased price of which is not showing a price at all?

5.5.5 Workflow of the experiment

During this experiment we measured all clicks and sales on the platforms which we use to buy traffic. These platforms are pricebots, but they also include search engine advertising and referring website which refer traffic to our site.

The goal of this last experiment is not only to find out the impact of position #1 of #2 in a pricebot, but also the sales which can be generated by advertising an a specific platform. Which platforms generate the most sales on a certain (discounted) sales price? See also the 4 goals formulated in the first section of this experiment.

To achieve the goals and to measure the hypothesis, we identified a number of products used for this experiment. Those products are placed in groups in order to measure more data compared to analysing a single product.

Prices of products used in this product are chosen carefully. First we analysed which pricebot could be used in order to measure sales prices of our competitors. Most of our competitors use multiple pricebots. The most-used pricebot in our branche is the Tweakers pricewatch. Most sellers in the Tweakers pricebot also advertise on Google, they use hardware.info and sometimes even Kieskeurig and Vergelijk. Because of this use of multiple pricebots by competitors, the Tweakers pricebot is used in this experiment to set our sales price. With this focus on Tweakers, we assume that our sales price is competitive compared to all other pricebots used.

We carefully chose position in the pricebot for this experiment. We grouped products based on this position in the Tweakers pricebot. The position in the pricebot was checked (and if necessary: modified) twice a day to make sure the position was maintained.

Position 1 in Tweakers Pricewatch: 26-09-2017 – 21-10-2017
112 sales

- Microsoft Office voor Mac 2016 Thuisgebruik & Studenten 1Mac
- Microsoft Office voor Mac 2016 Thuisgebruik & Zelfstandigen 1Mac
- Kaspersky Antivirus 1 PC, 3PC
- Kaspersky Internet Security 1 PC, 3PC

- Kaspersky Total Security 1 PC, 3PC
- G Data Antivirus 1 PC, 3PC
- G Data Internet Security 1 PC, 3PC
- G Data Total Security 1 PC, 3PC
- Windows 10 PRO (OEM)
- Windows 10 Home (OEM)

Position 2 in Tweakers Pricewatch: 26-09-2017 – 21-10-2017
1625 sales

- Symantec Norton Security Deluxe 3.0 NL/FR (1 jaar / 3 apparaten)
- Symantec Norton Security Premium 3.0 25 GB NL (1 User / 10 Devices)
- Microsoft Office 365 Personal NL
- Microsoft Office 365 Home NL
- Kaspersky Lab Kaspersky Internet Security 2017 (1 Gebruiker/User - 1 Jaar) Benelux
- Kaspersky Lab Anti-Virus 2014 1-pc 1 jaar

Position 3 in Tweakers Pricewatch: 26-09-2017 – 21-10-2017
565 sales

- Symantec Norton Security Standard 3.0 NL (1 gebruiker, 1 jaar)
- Symantec Norton Security Deluxe 3.0 NL (1 jaar / 5 apparaten)

We explained before, choosing a first position on Tweakers also implied a first position on Hardware.info, Kieskeurig and other pricebots.

5.5.6 Actual measurements

For the focus products mentioned above, we measured all visits and sales. The ultimate goals is not longer to determine best position in the pricebot (or other platforms) but to measure conversion percentages per platform. We measure how many clicks we received from actual human visitors and how many sales they generate. The logging of data is explained in the next section.

5.5.7 Data gathered & visitor identification

We used the basis of the tracking tool in the first experiment, but we modified this tool in order to measure all referring platforms instead of just pricebots that connect to our XML feeds. A welcome page was loaded in the background without the visitor noticing this page. In just a split-second this single welcome-page is gathering important data from the visitor such as:

1. IP address
2. Cookies from previous visit
3. Setting a new cookie to detect future-visits. Cookie lifetime is set on the max. value.
4. The price which was shown on the platform itself (based on a variable in the URL) when the referral was a pricebot
5. The HTTP_REFERRER to identify referring websites other than known pricebots.
6. The customers' session is recorded with a local storage object in the browser (client side). This local object doesn't have a lifetime, so it will exist for ever in the browser. When cookies are expired, the local object will continue to exist.

In addition to recognising visitors on their next visit, we also stored information we presented to the customer during each visit. For example; discount percentages, prices, number of products sold, end dates of a promotion shown etc. In our database, the visitor is given a unique ID. Based on this ID, we could offer the recurring visitor the same information on his next visit (or changed information, based on the experiment we are executing). In some experiments we can choose to modify information in order to measure how customers are responding to changes.

5.5.8 Assumptions and preconditions for this experiment

The great deal of pricebots is that visitors are very price-sensitive and willing to buy the product. However, now we include all other environments in our experiment we cannot compare or (or calculate/guess) the extent to which customers are willing to buy. We assume however, that on average people are equally motivated to buy our products.

On pricebots, the "reliability" of the seller is graphically displayed in a star rating (or equal representation) representing the average rating from previous customers. However, in this experiment we assume that all (potential) customers find our website trustworthy.

5.5.9 Goals and hypothesis

Goal 1: *Gather reliable clickdata from pricebots to match that data with our internal systems for analytics.*

ACHIEVED: This goal was already achieved on pricebots using our previous experiment and our previous measurement tool. Our improved measurement tool showed that it was also able to identify reliable clickdata from other external platforms (platforms other than pricebots such as Google Advertising).

Goal 2: *Measure the conversion for product groups advertised on a chosen position in the pricebot (i.e. cheapest or second-cheapest offer).*

ACHIEVED The tool provided insights in every click to a product on our website. Also all sales were recorded in our tracking tool. About 4-9% of sales (depending on the period used and products sold in that period) could not be linked to a referring platform, but for 90+ percent a referral was available and was measured. Within that 10% there is a lot of traffic from natural search results. Natural search is the "normal" search engine results without paying the search engine for a higher position.

The images on the pages below show the results of our measurement tool. They include all paid referring platforms. To make the image readable, other referring platforms are hidden. The images show the "overall" analytics in the period of 1 February 2018 until 18 February 2018. The image shows 57,4% of sales was from recurring customers. More than half our sales are from customers that renew their subscription.

The second-largest referring platform is Google Adwords. Adwords sponsored search engine advertising is 24% of all our sales. All pricebots accumulated (Tweakers + Kieskeurig + Vergelijk + Hardware.info) only result in about 7% of sales. Pricebots are generating only a very limited amount of sales compared to all other sources of traffic such as search engine advertising or customers acquired on natural search results. For more information, please see Figure 14 and Table 9.

In Figure 15 and Figure 16 the results from advertising a product on a position 2 or 3 versus a position 3 (or lower = more expensive) are shown.

- On a position 3: Results from aqcuiring new customers[1] are:
    - 17 from a total of 31 sales (55%) are from Search Engine advertising
    - 14 from a total of 31 sales (45%) are from Pricebots

- On a position 2 or 3: Results from aqcuiring new customers[1] are:
    - 25 from a total of 44 sales (57%) are from Search Engine advertising
    - 19 from a total of 44 sales (43%) are from Pricebots

In this case, we – again – observe a lot of our orders are caused by customers renewing their subscription (recurring customers). Because we have such a small amount of new customers, there is insufficient data to conclude about the usefullness of using pricebots on a pricelevel second position or lower. However, when 40% or more sales are still realised from pricebots on a pricelevel position 3 or lower, pricebots cannot be ignored.

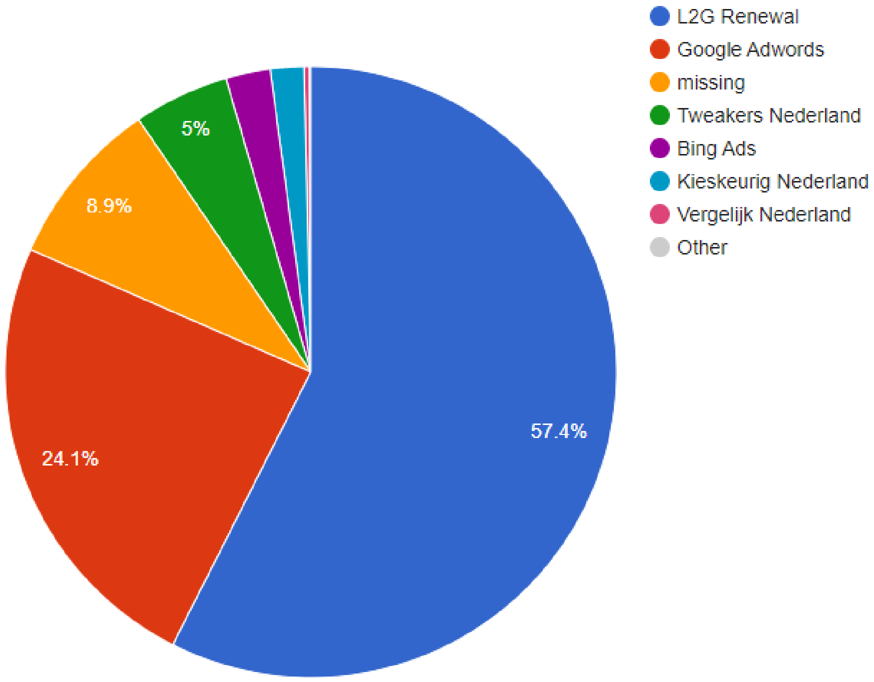


Figure 14. Average referring platforms detected in Experiment 3.

Table 9. Average referring platforms detected in Experiment 3

Totaal	**2209**	**100.00 %**
L2G Renewal	1269	57.45 %
Google Adwords	533	24.11 %
Missing	197	8.92 %
Tweakers Nederland	112	5.05 %
Bing Ads	52	2.35 %
Kieskeurig Nederland	39	1.77 %
Vergelijk Nederland	6	0.27 %
Daisycon Nederland	1	0.05 %
HardwareInfo Nederland	1	0.05 %

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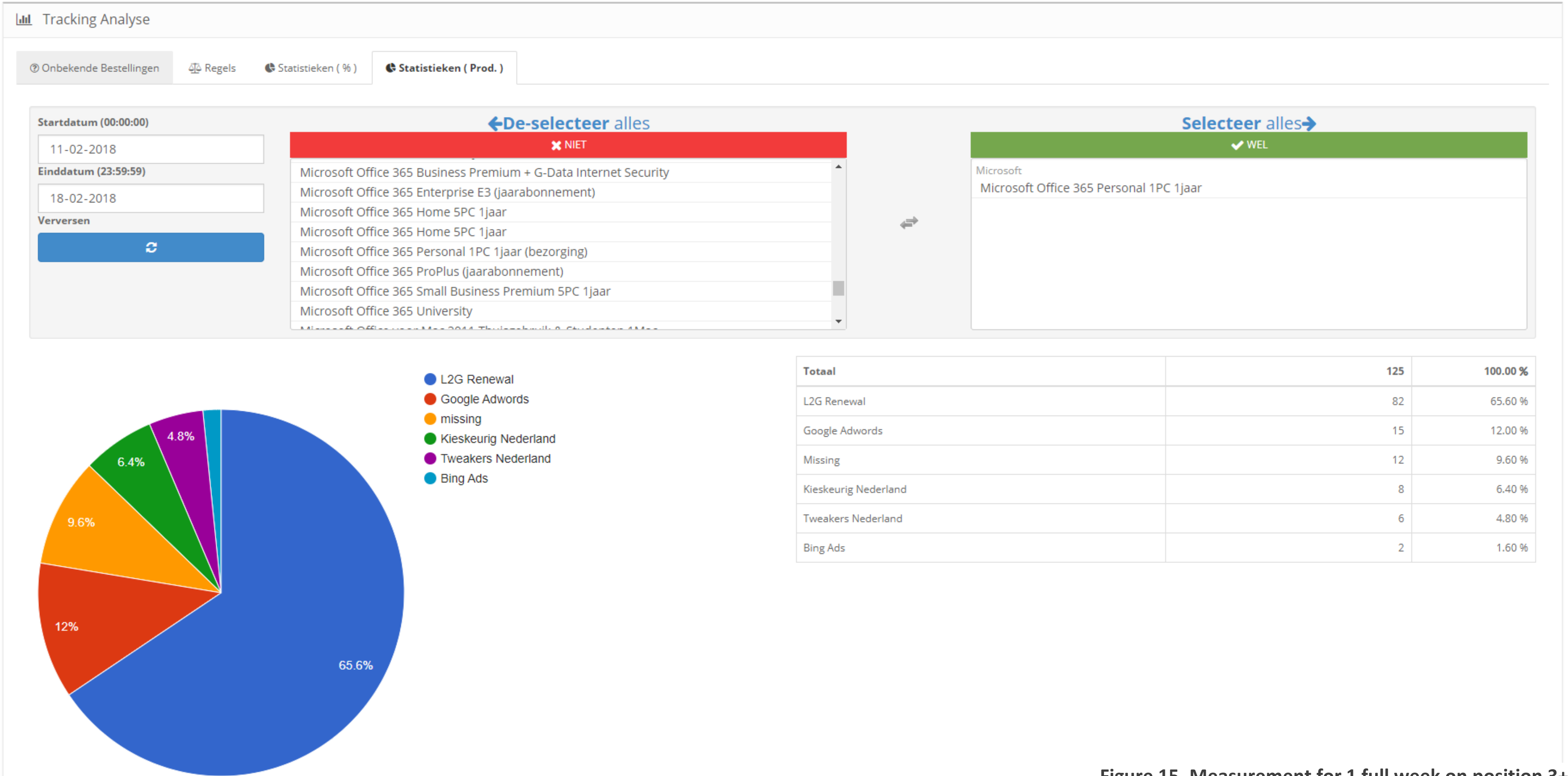


Totaal	125	100.00 %
L2G Renewal	82	65.60 %
Google Adwords	15	12.00 %
Missing	12	9.60 %
Kieskeurig Nederland	8	6.40 %
Tweakers Nederland	6	4.80 %
Bing Ads	2	1.60 %

Figure 15. Measurement for 1 full week on position 3+

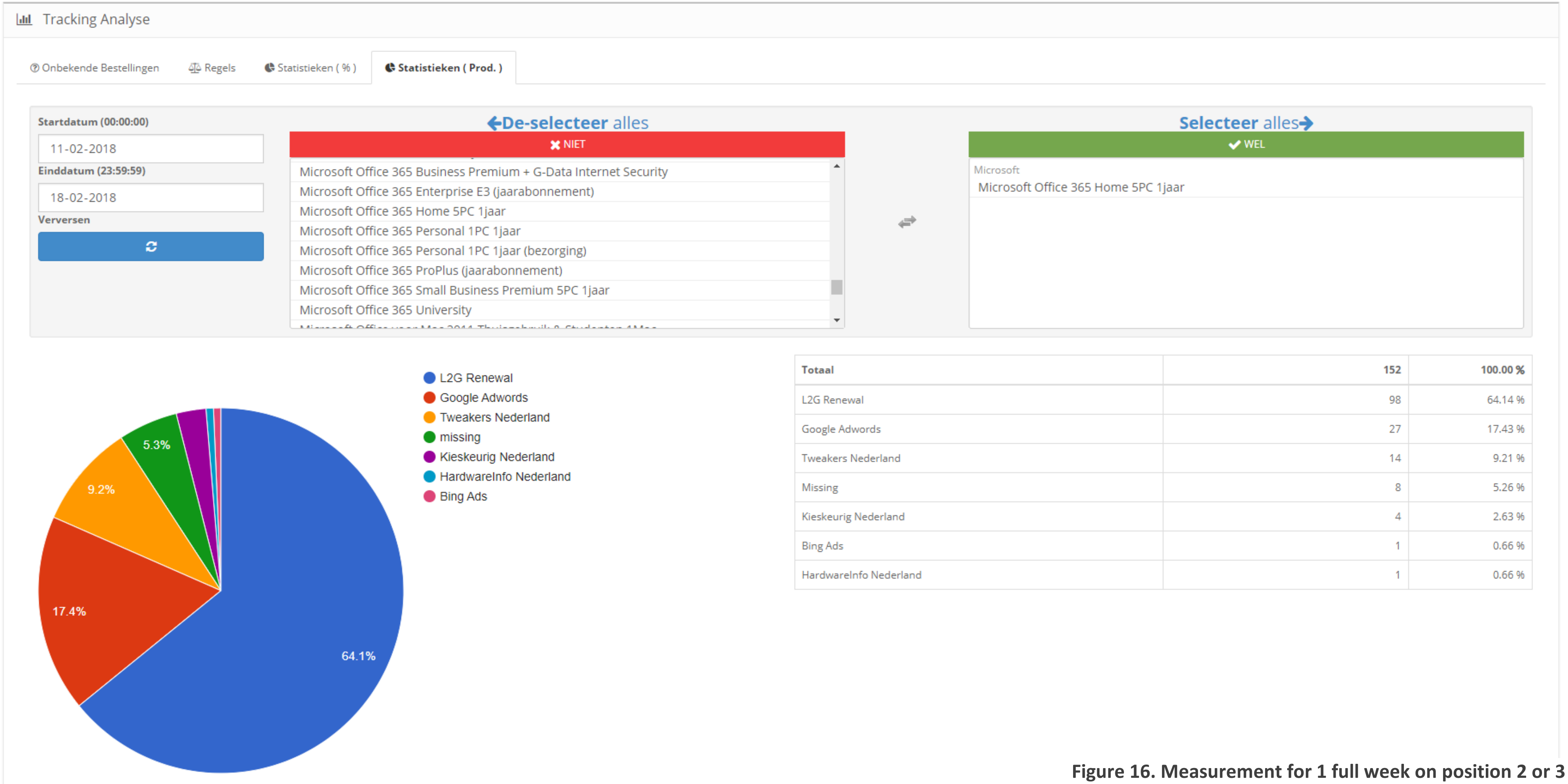
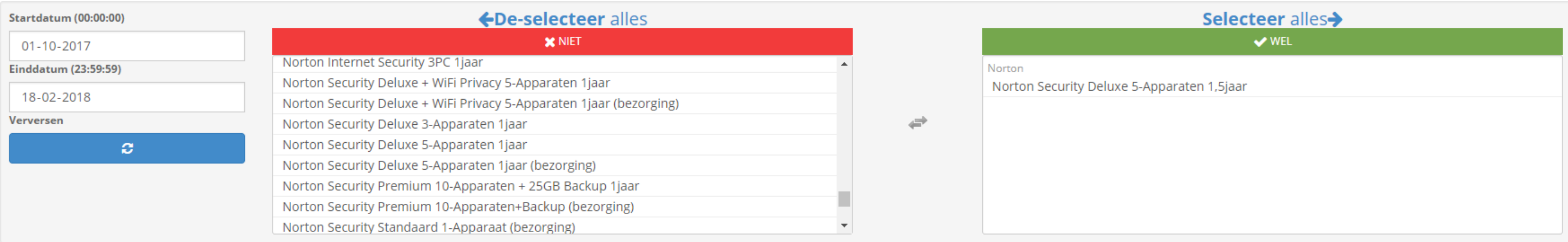
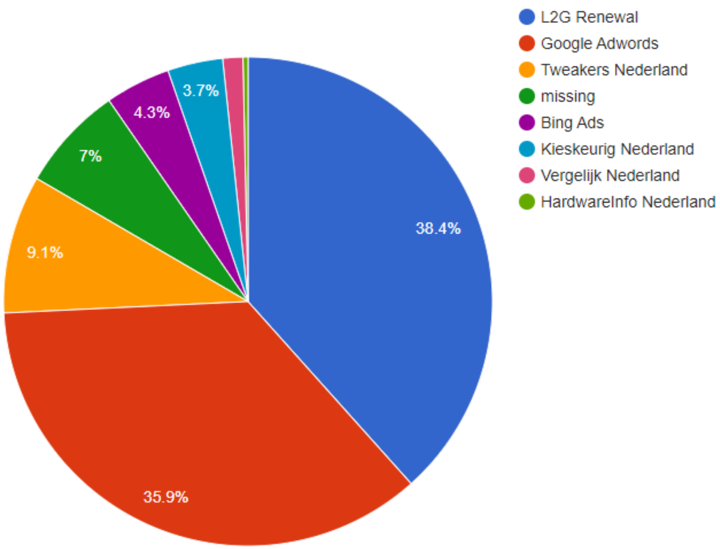


Figure 16. Measurement for 1 full week on position 2 or 3





Totaal	301	100.00 %
L2G Renewal	116	38.37 %
Google Adwords	108	35.88 %
Tweakers Nederland	28	9.14 %
Missing	21	6.98 %
Bing Ads	13	4.32 %
Kieskeurig Nederland	11	3.65 %
Vergelijk Nederland	4	1.33 %
HardwareInfo Nederland	1	0.33 %

Figure 17. Position 1: cheapest offer

The situation in Figure 17 might suggest that also when securing the first (overall cheapest) position, a pricebot isn't that usefull to advertise pricebots. The results: Only 44 out of 185 new customers can be linked back to pricebots. The largest group of "renewal customers" is excluded because they are recurring visitors which might have a different reference price because of their purchase of last year. We did measure how many recurring customers clicked on pricebots (after receiving the renewal-mail) but because of the very limited amount of clicks, we don't show the agregate data here (because it might display a faulthy representation of the actual situation).

The product used in this situation is a special product. The situation is:

- The product was introduced in 2017 as a special limited edition;
- There was only a limited stock available for a small period of time;
- Licentie2GO bought all remaining (Dutch) stock in order to gain a monopoly on this product.

With this situation, the product has only had limited attention to the public. There was limited visibility in pricebots, limited traffic on natural search results in Google and because of this the bulk of sellers that is normally optimizing for Google isn't acting on that for this product. Therefore, we might experience lower traffic via pricebots because lack of investments resulted in lower audience via pricebots.

For the best results; the measurement needs to be repeated over a longer period of time using another more important product. No limited edition products and no products being at the end of its lifecycle. Measuring over a longer period of time, establishing an equal position in the pricebot will give a better answer on the usefullness of position 1, 2, 3 or lower in the pricebot.

> *To gain more new customers on a lower price level, Licentie2GO is soon launching a new brand name especially designed for pricebots. The new brand is advertising on pricebots just to beat other providers' pricing. The model should be able to attrackt more customers without losing the margin optimization in the Licentie2GO-pricing-model.*

5.5.10 Answering on other hypothesis

For answering the hypothesis, we will not repeat the hypothesis from our previous experiments. Repeating is useless because our new tool was just an extension of our previous tool. Because we re-use the technique from our previous experiment, the results will be the same.

H3 *Position 2 in the pricebot[2] with a high price-difference (> 0,50 EUR) will result in almost no sales compared to position 2 with a small price-difference.*

Using our new measurement-tool we are able to measure all referring traffic. The aim was to measure the impact of position 2 in pricebots, however a greater piece of information was found measuring with our new tool. Position 2 in the pricebots generates less traffic than position 1; that's what we measured. However, we could – due to insufficient data – not conclude on the conversion rate of position 2 versus position 1.

Moreover, measuring all positions in the pricebot AND the traffic from other sources, a more interesting result was found. The traffic from other sources combined is generating more traffic and more revenue than the traffic from pricebots. Therefore, it should be wise to develop distinct pricing strategies on pricebots compared to the pricing strategy for other referring platforms.

H4 *The conversion on pricebot A is considered to be comparable to the conversion on pricebot B when an equal price-level is set on the platforms.*

Because our new tool recorded more data from all other platforms, we can obviously conclude that all platforms have different conversion rates for different product combinations. Over a period of time, using the same product (groups) on the same pricebots we expect a stable conversion rate to be detected. However, more data from pricebots is needed to prove this statement. On this very moment pricebots don't deliver a quantity of traffic that is high enough to conclude on this. In addition; Licentie2GO isn't able to maintain a stable position in pricebots because it is very hard to continuously measure our competitors pricing.

Note; hypothesis 5 – 7 are skipped in this experiment because they are already answered using our previous experiment. The same technique is present in this research so results are equal.

H8. *Using our wall of entry, we can measure the number of pricebots used by visitors to compare the product before making the actual purchase.*

TRUE. See previous experiment for more information. The exact measurement and outcomes were recorded in this experiment.

H9. *Using our improved wall of entry, we can identify sources of entry that visitors use to visit our website without having to setup those platforms using tracking cookies or any other manual action.*

TRUE. Our previous experiment was able to measure all linked pricebot platforms, but in this experiment we also added other referring platforms that are stored. In this experiment we are able to identify all pricebots used AND all other referring websites that are used based on the HTTP_REFERRER in the browing history of the user.

H10. Using our improved wall of entry, we can identify the total amount of clicks from robots (non-human internet traffic) from paid referrals to our website.

TRUE. Our improved tool recorded the header of the browser just like we did in the previous experiment. Using our improved measurement tool, we can measure bots entering our websites from pricebots, but also bots entering our websites via all other referring platforms.

H11. Using our improved wall of entry, we can calculate the minimum margin per product- or product group based on the conversion rate on the referring website.

Would be possible. Using our wall of entry, we can by a high degree of certainty measure where our customer base is coming from. Using the origin of our customer base, long-time statistics on the conversion rate for product (groups) based on a certain pricing level on the platform of origin, an optimum overall margin can be calculated. However, it requires a lot of (long-term) data.

5.5.11 Optimizations for next experiment

From this experiment we learned the importance of knowing the entry points of visitors. Continuously lowering prices in order to have the cheapest offer isn't a sustainable business model when it doesn't increase sales. The increase in sales should be measured on the platforms where the decreased price is advertised.

With our measurement tool (used in this experiment) we are able to detect recurring visitors. The great advantage of this is that we can implement dynamic pricing. Every recurring visit can be used to change price (or other variables on site) in order to encourage the visitor to buy the product. Dynamic pricing, measuring and changing such variables should be used as a basis for the next experiment. A lot of optimizations can be implemented by measuring recurring visitors. The current statistics show that the time from first entry until completed purchase is about 3 days so it is likely that margin can be optimized by pursuing customers to complete their purchase in a shorter amount of time.

6 Experiments linked back to research questions

The experiments conducted at Licentie2GO helped us gaining insight in e-commerce in general, but more important learned us about dynamic pricing in e-commerce and the endless possibilities for the use of measurements to optimize online advertising. The most important aspect appeared to be segmentation and the origin of customers.

To help us finding answers on the research questions defined before, some assumptions needed to be made during the experiments. There were more variables involved in the experiments than we could explain or measure. Some variables (see sections 5.3, 5.4 and 5.5 for more details) have been assumed to be equal during all experiments. Other variables (such as user reviews) are explained to have a relation to the outcomes of our experiments, but they could not be involved in our measurements.

Every experiment is referring to the assumptions made. Every assumption and precondition is mentioned in the experiment in order to make sure future researchers have the information about which impact the assumptions might have had on the results found in this thesis.

The experiments are contributing to research questions and to open gaps in literature by providing a practical insight in the operations of a mid-sized e-commerce business. The data found and the lessons learned from the executed experiments can be used in future researches. A major important lesson learned here is that measuring data is only the starting point. Our research points out how to mitigate measurement-errors to come to reliable results. However, a lot of traffic and major numbers of visitors are needed to draw conclusions on the research questions asked.

In general, the variables measured and the results we have gained by executing the experiments are valuable for this research because they help in answering our research questions. For more information about the limitations, see chapter 8. For more information about the outcomes, please continue reading the next sections.

7 Main conclusions: Research questions answered

In this chapter, the main conclusions are presented based on the research questions we stated before. The research questions are repeated below and are answered one by one.

RQ: How can we maximize the results of online advertising using dynamic pricing, in a mid-sized web-shop selling digital software.

In order to answer this research question, three sub-questions were formulated. The sub-questions will be answered before answering the main research question.

7.1 Platforms and advertising-strategies.

SQ 1: Which platforms are used to advertise products and which (pricing-) strategies are available on these platforms?

The organisation assumed that most of the revenue was made by advertising products in pricebot platforms. This was the starting point of this research by executing experiment 1 in order to find out which platforms are used for advertising. For more information about the experiments, see section 5.3, 5.4 and 5.5 for more information about the experiments.

It appeared that pricebots were generating only a limited number of human visitors and sales to the website. The last experiment (experiment 3) implemented a wall of entry in the website in order to measure the last visited referring website. This showed that a number of categories could be defined for referring traffic. The categories of referring traffic and their pricing strategies on which most sales were generated per platform are shown in Table 10 below.

Table 10. Concluding remarks on customer segments and suggested pricing strategy based on knowledge from literature and from experiments executed in this thesis.

Platform / category	Pricing strategy
Pricebots I.e. Tweakers, vergelijk.nl	1. Offering a product at a low price. 2. Choosing pricebots with a lower level of competition. 3. Standing out above the rest by advertising in the pricebot, achieving high user reviews or delivery times shorter than other providers in the pricebot.
Search Engine Advertising I.e. Google Adwords, Bing advertising	1. Highest bid in order to achieve top-position. 2. Standing out above the rest by creating unique adds. 3. Finding an optimum in bid versus margin on products sold.
Natural search engine search Scoring higher in natural (free) search results.	1. High sales prices can be justified because of more visitors without additional costs. Sales price should be competitive among other high-scoring providers. 2. The price should match the position in the search engine. High results should have a high price (in order to win back the costs of optimizing for this high position), lower position can have a lower price.
Referring websites i.e. Blogs, test-reports (consumentenbond) etc.	1. High sales prices are justified because consumers gain trust by the referring provider. 2. Competitive offer in order to compete against other referred websites.

Our wall of entry was able to detect traffic sources. Based on the results of this wall of entry, the table above was created. The table showed that 4 large categories could be found which are in use for advertising products to potential customers. The table only concludes on a strategy for platforms that generate new customers. Recurring purchases are out of scope.

7.2 Contributions per advertisement-platform

SQ 2: How can we measure the contributions per platform to revenue and profitability of the business?

The contribution of a platform referring visitors to the businesses' website to revenue and margin, appeared to be very dependent on the price of a product. A product which could be sold very cheap compared to other sellers was doing pretty well in pricebots. A position 1 or 2 appeared to gain a lot of visibility in the pricebot and as a result also a much higher amount of sales compared to lower positions. Offering a low (but: reliable) price appeared to be the only way to stand out in the ranking of pricebots.

However, efficiency of pricebots is varying enormously based on the position of a price (the level of competition) on each pricebot. A tool was designed and implemented during experiment 2 in order to measure efficiency of each pricebot, see section 5.4.

In all cases, expensive or cheap products, a much more important platform for advertising products appeared to be Search Engine advertising. Advertising products in search engines was not only generating more traffic for the business, it also provides the ability to sell products with a higher margin compared to selling products in pricebots competing for the cheapest position. For more information and detailed analysis on this results, see section 5.5.

The analysis and measurements represent the current business situation. Our tool is able to detect and cope with changes on all platforms. It might be possible that providers stop advertising on pricebot-platforms or that other external factors change which can change the ratio of visitors using a pricebot versus Search Engine advertising.

Last but not least; the direct traffic from customers renewing their subscription was the biggest contributor to margin. It provided revenue without advertising costs. Existing customers made a recurring purchase for renewing their subscription. The current strategy to focus on customer retention is – based on the knowledge gained in this research – a clever strategy.

In a next experiment an investigation can be done in order to find the ideal sales price for renewing-customers. In the current situation, renewals are offered a discounted price lowering the margin. Possible future work could be to find the price at which for example 90% of a customer segment (or any other chosen percentage) is renewing their subscription at an increase price compared to the current price-level. This reference-price-research can have a major additional impact on revenue, but is not without the risk of losing customers.

The improved wall of entry presented in experiment 3 will help the business in finding the sources of referring traffic. It shows the amount of referred traffic, the contributions of that traffic to revenue and margin in a predefined period of time. The tool provides continuous measurement which is able to help the business in continuously improve the sales and margin from a specific referring platform.

7.3 Optimize advertising- and pricing-strategy

SQ 3: To what extend can we optimize the advertisement- and pricing-strategies on the platforms used to increase revenue and profitability?

Our measurement tool was able to detect all sources of traffic. Orders placed can – using our wall of entry – be traced back to a traffic source. In addition; when we know the number of orders from a traffic source, we can extend our model by doing some trend analysis. By measuring trends in increasing/decreasing sales of certain products, the optimizations can be implemented in marketing activities or in product pricing. The trends may be detected by measuring the number of clicks from platforms and the number of sales. By using a dynamic pricing strategy, we can measure an optimum in the number of sales per 100 clicks (that is called: the conversion rate) under a certain price point.

The source or traffic; the original platform, is an important factor in determining the optimum sales price. A platform such as antivirus.nl (used in our experiments) is experiencing no (or at least: a lot less) changes in the number of sales under changed price conditions. Antivirus.nl is helping customers to find the best antivirus product for their situation. Price isn't the deciding factor for the customer when he is looking for the best product. The situation changes on a platform like Kieskeurig or vergelijk.nl. Those platforms are comparing equal product from multiple providers. The deciding factor in such a comparison is price (and probably some other conditions that we haven't measures, possibly like delivery time, review rating).

The balance between the advertising strategy (and thus: advertising locations) and price is an important factor for achieving more results from online advertisements. When matching the pricing strategy (choosing an appropriate sale price) to the advertising strategy (choosing the best location for advertising products) businesses' can experience the best results.

Dynamic pricing

To achieve an optimum margin – that is: the best price on each advertising platform – dynamic pricing can be used. Our theoretical research found out that a lot of dynamic pricing is to be used these days by all kinds of organisations. A framework for big data analysis is under development right now by the organisation. The framework is built on 2 main strategies:

1. Handle prices on pricebot automatically; Because of the heavy competition and the ability of pricebots to generate traffic that cannot be referred to the company's website other than by using (and paying) the pricebot, we have to operate on a pricing strategy that is suitable to support the business strategy. If the business strategy is to grow and attract new customers, the organisation might (automatically) match or beat the price on the pricebot. Another option is to operate on such a level that the organisation is able to gain a maximum revenue out of the pricebot if the business strategy is to generate a healthy margin. This can be done by choosing a price on position 2 or 3 that is able to generate traffic, but is on the same time generating an optimum amount of total margin (see strategy by Ghose and Yang [22] in literature). A technical experiment is built into the framework to test several prices in order to achieve the optimum price.
2. The alternate large categories of traffic are SEA, SEO and referring website. For those categories, dynamic pricing is not to be focussed on competitors, but on converting the visitor. For example; dynamic pricing might be implemented by decreasing the price on a recurring visit (already implemented and tested) and dynamic marketing might be implemented to gain a higher conversion rate based on the search query the customer used to find the company's website.

7.4 Main research question answered.

RQ: How can we maximize the results of online advertising using dynamic pricing, in a mid-sized web-shop selling digital software.

In order to maximize the results of advertising, the most important aspect is to measure the inputs and outcomes of advertisements. Because traditional measurements didn't comply with our information needs, in this research we designed a new measurement tool. The tool was able to filter results and to match the outcomes of advertising (basically, results are: a bunch of visitors bought to the website at a certain cost) to platforms of origin. This type of segmentation appeared to be useful to the organisation to design a better pricing strategy.

By segmenting customers and advertisement-results per platform we were able to optimize the advertising-efforts per platform. The business used for executing our experiments (Licentie2GO) was focussing on profit maximization, so when focussing on "optimizing the results of online advertising" our outcomes should comply to this business-goal. This goal was achieved due to improved revenue and improved margins after implementing the designed tools.

Please note that other organizations might have other business goals (for example; market penetration) and thus they might have a different direction of optimization. Our tool is able to support optimization among multiple business goals because we not only measure profitability of advertising but also visibility and impact of advertisements. The tool gained insight in the amount of visitors per platform, pricing level of platforms (and pricebots) and in some case even the costs and ROI of advertising on advertisement platforms.

We experienced (see section 5.5) that – besides global optimizations in advertisements – a lot more detailed, more effective and more efficient optimizations could be achieved when optimizing advertising on a "per-platform"-level. By matching the pricing strategy and advertising strategy per referring platform, a maximum profit could be achieved. The business is advised to dynamically adjust prices per platform in order to set an optimum price. By doing that a maximum number of new customers are attracted and at the same time no profit is wasted by setting a price that is too low compared to other providers on the same referring platform.

Last but not least; matching the advertising- and pricing-strategy is always related to the business strategy. A business offering all products at discount prices, should never envision selling products very expensive at some chosen platforms. This strategy doesn't link back to the business strategy, making it unlikely that marketing-materials (i.e. the website) match the more expensive offers at specific platforms and in result customers remain confused. Having such a mismatch is devastating for the results of the campaign making it much harder to optimize. In short; despite we focussed this research on optimizing advertising- and pricing-strategies together, please note that these strategies are always related to other business levels and should also match the other levels of the business.

8 Limitations and future work

In this chapter we look at the limitations which might threat the validity of this research and we'll look at this research' contributions. Later, we'll introduce some future research and future optimizations.

8.1 Limitations

A few limitations to this research should be noted to explain the validity of this research.

1. During the experiments we made some assumptions in order to make sure we had a workable situation. Not all variables could be measured and evaluated, therefore these assumptions were required. For each experiment, these assumptions are noted in the experiment itself. Each assumption might be a reason for further investigation in future research.
2. All pricebot platforms have their own internal competitive environment. That means; not all pricebots have the same records for competitors, products and price making the competitiveness per platform a different situation. In that respect, we must note that a different price level on pricebots might lead to different conversion levels. Most competitive for software products is the Tweakers pricebot. For example, Hardware.info and Daisycon are platforms that have less competitors among software sellers today (maybe because they are not able to draw a lot of natural search traffic to their pricebots). This might imply less competitiveness and thus a higher conversion rate from those platforms. It might also flip to the other side in delivering visitors with less intention to buy (lower willingness to pay) because the platforms simply don't specialize in software, which might lead to lower conversion. In next researches, this issue can be looked into more closely leading to more data and better analysis.
3. Despite the validation of our work is done by informally asking some field experts, this research still is one of the first published researches doing practical analysis in a live web shop. We informally asked some experts on our strategy and discussed some results, but because of the informal character of the meeting, the discussion is not in this thesis. In addition; despite the increased revenue and margins at Licentie2GO, there is no proof that the same will happen when executing this research in another organisation (however we expect our work to be at least useful to other organisations).
4. In this work only a limited amount of time was available to gather measurement data. Because of the scope of Licentie2GO, we only measured data on a small web shop selling software which might not be generalizable to other webshops.
5. More field research in larger webshops (preferable selling more than just digital products) is needed to gather more data. The main problem with this research is the lack of quantity in data. Some directions to find solutions to open questions are presented in this work, however more data is needed to provide reliable proof on this.

8.2 Future research

A lot of research in still to be done when researching a broad area of maximizing the results of online advertising. Below four areas of future research are presented. These four areas are directly available for other students to be research in our organisation (Licentie2GO). However, the research subjects are broadly defined in such a way that these researches can be executed in every other mid-sized e-commerce organisation. The last mentioned research (dynamic marketing) is already in development in our organisation as a follow-up of the present research. However, for this paper the subject is out of scope and therefore not defined in more detail.

8.2.1 Long tail margin optimization strategies

Long tail margin optimization strategies may help to sell unique products in the assortment of the business. The advantage of using a long-tail strategy for the business is that long-tail products usually are less available or less easy searchable in pricebots. The reason for this is that pricebots normally use the SKU or EAN code which is mentioned on the box for comparing products. Long-tail products are usually not sold in boxes causing the pricebots to leave with no fixed value for matching the same products for multiple sellers. As a result; long-tail products have to be sold using other advertising techniques than just selling them in pricebots. For example, products can be sold by recommendations to existing visitors, using search engine advertising or by displaying and recommending long-tail products as related to other products on the shop. Using those strategies, long-tail products can have a great contribution to the profitability of the web shop.

8.2.2 Margin optimization strategies for recurring-customers

Margin optimization strategies for existing (renewing-) customers may be investigated further. Manufacturers of the products sold by Licentie2GO already researched such strategies. The product manager of Norton (market leader for consumer security products in the Netherlands) told us that a price increase of 10 EUR per year, resulted in a drop of 2% of the renewals. For the most expensive product, 10 EUR is a price increase of 10%, for the cheapest product that is 25%. A drop in sales of 2% appeared to be no problem in such a situation when the strategy of the organisation is to focus on high margins. Licentie2GO may perform the same research in order to optimize margin from existing customers renewing their subscription at Licentie2GO. The model followed by Norton is in line with the findings by Lau and Lau [39] who executed a similar research combining an increased product pricing with the optimum return policy.

Literature research on such strategies are already indicating positive results. For example the work by Cope [12] tested a margin optimization strategy based on the relation between expected demand for a certain product at a given price. Cope found that a learning strategy in which the demand forecast was optimized by measuring customers' response to price changes worked best. Such a strategy is categorized as a Bayesian optimization strategy which is indicated as successful by more researchers. For example, the Bayesian strategy by Abe [1] to find the optimum price for a private label against a national brand or the highly researched "newsvendor-problem" (i.e. by Agrawal [2]). Newsvendors having unsold papers at the end of the day phase a worthless pile of inventory. By changing prices during the day they might optimize margins to sell the exact amount of inventory at fixed prices. Also in other sectors there is knowledge available to learn from. For example, in grocery stores [69] (perishable) goods need to be sold in a certain period of time at the right price, airlines and the hoteling industry having pricing strategies to optimized their occupancy at the right pricing. By learning from those industries, e-commerce organisations (i.e. Licentie2GO) can optimize their revenue by applying self-learning pricing technologies.

8.2.3 The relation between marketing-, advertising- and pricing-strategies.

The relation between optimizing marketing-, advertising- and pricing-strategies may be investigated in more detail. A field research might be performed (i.e. with A/B-testing) in order to measure the best way to show and sell products on a webshop. For example; displaying a price in a renewal mail might optimize sales, but it can also result in decreasing margins. The way an e-mail or website is presented (marketing) might be of great importance to convince customers to buy the product. When done properly, good marketing might heavily increase sales, however poor design is leading to decreased sales and thus decreased margins.

Previous research already indicated important relationship between marketing and pricing. For example, Degeratu [14] researched consumer choice in supermarkets looking at the relation between brand name and price. Others investigated reference prices to certain brand names to determine the relation between marketing and pricing (i.e. Miraldo [51] and [4]). Moreover, an established brand is set to have a certain brand recognition realising increased trust and thus faster- and more recurring transactions [29], [3].

8.2.4 Dynamic pricing vs. dynamic marketing

As part of investigating the optimizations in marketing-, advertising- and pricing-strategies, a dedicated research can be performed on dynamic marketing. Changing the sales price of a product was already proven an interesting strategy by previous researchers. Also in this research dynamic pricing appeared to be helpful in pushing customers to realising the sale. However, one might perform dynamic marketing in order to increase margins for recurring customers. By increasing or dynamically adjusting the marketing-promises on a next visit, customers might be pursued to realise the sale in the same way like dynamically adjusting the price. Dynamic marketing might be applied to predefined customer groups using A/B testing. By continuously looking for the best marketing approach the business might be able to better understand customer needs in terms of marketing. In that respect, the business might adjust the marketing to areas of interest to specific customer groups which in turn might lead to a better fit between customer needs and the businesses' offer justifying a higher sales price.

8.2.5 Customer retention by bundling product- and service-offers

In the current situation, Licentie2GO is one of the e-commerce sellers offering a product range that can be bought elsewhere. The company strongly believes in the current Unique Selling Points (USP's), but the business should be able to achieve an even stronger position.

The last area of future research to be mentioned here is based on a research performed by Yang [71] on dynamic pricing in the telecom industry. Telecom providers (also in the Netherlands) are more and more bundling products and services in order to increase the customer value (in terms of monthly revenue). Dynamic pricing is applied here by implementing a discount on 1 product, when a second product from the same telecom provider is bought. Discounts on such bundles is an interesting case of future research.

E-commerce organisations often implement upselling and cross-selling strategies to achieve this. Due to the nature of Licentie2GO as a technical business selling software products in good cooperation with software manufacturers, the business might be able to generate a vendor lock-in in the customer-base when having a unique product- / service-bundling. Strategies around unique products are already tested in this research using dynamic pricing in pricebots (see section 5.5.9), but future research can be used to find out how to design the ideal product- and marketing-mix to achieve higher customer retention rates.

8.3 Future Development

8.3.1 Suggestions for an optimization model in future research

In this section, we suggest an optimization model on achieving the highest profitability using our improved wall of entry measurement tool. These suggestions are based on knowledge we gained during the experiments and might be a starting point for future researchers.

When changing prices on different platform (sources of visitors), some suggestions will be worked out below for finding the best pricing strategy. Models to be used as a basis for optimizing price can be based on for example marketing decisions, but they can also be financial based or be focussed on finding more customers. The results below are found during our experiments in the business of Licentie2GO and might be valuable for other businesses.

The results below are not evaluated in detail, nor are they proven using analytical outcomes of our experiments. They might be subjected to future research in order to prove the validity of our suggestions. For proven results of our research, see chapter 8.

1. Using a model like NPV-model (Net Present Value), one may calculate to what extend lowering the price of a product is resulting in more orders. More orders in a short period of time is freeing up the money that is stuck in inventory. The NPV is taking into account the time value of money. First, the money is of no use when it is stuck in inventory. When products can be sold faster at a lower price, the money becomes available again for doing business. Second, when there is a shortage in working capital, money needs to be borrowed. Borrowing money is costing money, so an NPV-like model should be used in order to take into account the interest that should be paid. Time-value of money is probably the most important aspect for a decision to optimize the profitability of the business.
2. The business can decide to lower prices from a marketing-perspective. For example; lowering prices for a “Norton Security” product can be good in order to attract more customers for the Norton-brand.
3. The business can decide to lower prices from a competitive perspective. When an important competitor is lowering prices, it can be good to lower prices along with that competitor in order to make sure customers don’t change to that competitor. In addition; when a competitor is lowering prices the reference price for that product may be lowered. In order to retain market share, the business can decide to lower prices along with the competitor.
4. The business may decide to increase prices in order to retain or increase operational margins.

9 Contributions

In this chapter, the contributions of this research are discussed. At first, the contributions to the business are described, followed by a generalization of contributions which can be applied to other businesses. Last, contributions to literature are worked out.

9.1 Contributions to Licentie2GO

Licentie2GO is practising a ***margin-optimization strategy***. However, when we started this research, the general pricing strategy was: low pricing following the most important competitors price point. During this research, we found out that the pricing strategy should be adjusted so that it can support the business strategy in optimizing margins. The misfit between advertising strategy and pricing strategy should be resolved. In this chapter we will argue why the pricing strategy should be adjusted. Based on the work executed in this research the tools and information are available to change prices.

a) Licentie2GO should determine the sales price of products on the large entry points of visitors, not just on the largest pricebots in The Netherlands. Based on large entry points, the price-level and pricing strategy should be redesigned. Possibly prices can be raised without losing customers or lowering the amount of new customers to be attracted using the same level of advertising.
b) Licentie2GO should execute an experiment in raising the price for renewing customers in order to find out how many are dropping out and renewing their subscription elsewhere. An optimum should be found in optimizing margin versus trying to retain 100% of the customers by undercutting prices. In that respect, an increase in margin can be achieved just by finding the optimum sale price.
c) Key to optimizations in the business is the tool to measure the initial entry points of visitors. The tool is really valuable to the business in order to measure entry points and to match the pricing strategy to the advertising strategy. The business is advised to keep using- and improving this tool in order to continue the measurements.

Most important contribution to the business is not the measurement tool, but the outcomes of the tool. The outcomes resulted in increased profit, better focus on important advertising platforms and a better fit between platform and price.

9.2 Contributions to other businesses

9.2.1 Dynamic pricing- and advertising-optimizations for Mid-Sized e-commerce organisations.

Besides the company-specific outcomes, the results of this research can be evaluated in a broader context. Of course Licentie2GO experienced improvements in their business, but the aspects found can be implemented in more businesses. Most medium-sized e-commerce organisations phase the same problems during their growth phase making the outcomes of this research applicable in a broader context. For example; it is not unlikely for fast growing organisation climbing from a small starting web-shop to a mid-sized organisation to have high revenues without making any profit.

Mid-sized e-commerce organisations can learn several things from this research. Besides e-commerce organisations, the items below are also applicable to other (mid-sized) businesses however they are not tested in a context without e-commerce as a primary sales channel.

1. An advice to all growing businesses is; measure the sources of Internet traffic. Knowing traffic source is crucial to the business for knowing the types of customers the business is servicing. Types of customers might have different requirements for satisfying customer needs.
2. When knowing the sources of traffic, all businesses might use our model for optimizing revenue. In addition; when businesses have other high-level business goals then optimizing margin, other goals might be used. For example; our tool works perfectly with a business goal like; achieve the highest growth in terms of attracting a maximum number of new customers or for example, making sure the customer retention is at the highest rate.
3. Businesses should carefully design their added value and chose an appropriate pricing strategy. That means; they should know their price range and they should define a clear marketing-model to defend the added value. After that; businesses should design an appropriate advertising-strategy; They can use our model to measure results from the chosen platforms used to advertise products.
4. The direct costs of advertising (part of measuring the advertising model) should be tracked back to the revenue model. Knowing the (average) direct costs per sale per platform can be used to optimize the pricing model. Most likely, every business should experience a different cost per customer acquired per advertising platform used. These costs can be used by design a profitable dynamic pricing model adjusted specifically to the advertised platform.

9.3 Contributions to literature

This research demonstrated the use of dynamic pricing and the optimization of advertising technologies in a mid-sized business. The measurement tools used in this research can be a valuable contribution to further researchers investigating the same situation in other businesses.

The use of dynamic pricing in businesses was described before in literature, but this research adds measurements and realistic data to the research field of dynamic pricing in e-commerce. Lots of researchers wrote before about dynamic pricing under inventory considerations, but in this example, no restrictions or devaluation of inventory was present adding a slightly different example to existing literature.

This research also demonstrates that a one-size-fits-all dynamic pricing approach can be extended by adding more segmentation. More segmentation means a better fit to the customer resulting in a better service for a better price. The research also acknowledged some previous statement in literature. The data found in our measurements providing acknowledgements on the statements below, can be found in the appendix.

1. A fit between (1) the business strategy, (2) the marketing-strategy, (3) the advertising strategy and (4) the pricing strategy leads to more sales at lower costs.
    a. More sales at lower costs is equivalent to increased margin.
2. Backwards segmentation (segmenting customers in groups after the order was realised) can be very helpful in optimizing the pre-sales fit between the business strategy, (2) the marketing-strategy, (3) the advertising strategy and (4) the pricing strategy.
    a. Backwards segmentation gives the business the information that is needed to adjust marketing-, advertising- and pricing-activities in order to fit the business strategy.
    b. The information gathered by using backwards segmentation is basically where customers found the website and gives information about their “willingness to pay”.
    c. In addition; the referring platform is an indicator for the price-sensitiveness of the customer. This information about price sensitivity can be used to optimized margin or optimize marketing in order to realise the sale.
3. The “willingness to pay” is strongly correlated with the information on the platform of origin of the customer. For example; willingness to pay is proven to be much higher on pricebots than the willingness to pay on the blog “antivirus.nl” which is more informative about security solutions.
4. Based on the willingness to pay combined with backwards segmentation, businesses should be able to optimize the fit between the 4 strategies. Optimizing the fit may lead to optimized pricing using 1 website on multiple platforms or may lead to setting up different websites to advertise 1 website per pricebot in order to generate a maximum number of sales on the highest possible price.

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Appendix A: data gathered in the experiment 1

The table below is an example of the data gathered using the combination of data. The green rows show a conversion rate above the average number in that period of time. A position (based on Tweakers pricebot) and distance against other offers was chosen carefully. The data in this first experiment is raising questions about reliability. The conversion rates differ (a lot) when we compare platforms. In addition, the quantity of data is very limited making it hard to draw any conclusions.

	Vergelijk			Tweakers			Google Adwords					
	#clicks	#sales	Conversie (%)	#clicks	#sales	Conversie (%)	#clicks	#sales	Conversie (%)	Price	Position	distance
12-8-2017				7	3	43%	7	0	0%	€ 37,55	1	€ -0,01
11-8-2017	8	0	0%	8	4	50%	9	0	0%	€ 37,64	2	€ 0,10
10-8-2017	12	0	0%	4	0	0%	5	1	20%	€ 40,29	2	€ 3,30
9-8-2017	7	1	14%	8	1	13%	13	2	15%	€ 40,29	2	€ 3,30
8-8-2017	12	0	0%	5	1	20%	4	2	50%	€ 40,29	2	€ 3,30
7-8-2017 (avond)										€ 40,29	2	€ 3,30
7-8-2017 (ochtend)	5	0	0%	1	1	100%	3	0	0%	€ 38,21	1	€ -0,10
6-8-2017	4	0	0%	6	0	0%	3	2	67%	€ 40,29	2	€ 3,90
5-8-2017	9	0	0%	7	2	29%	3	1	33%	€ 40,29	2	€ 5,28
4-8-2017	2	0	0%	4	2	50%	10	1	10%	€ 37,15	2	€ 1,48
3-8-2017 (avond)				8	4	50%				€ 37,15	1	€ -0,02

3-8-2017 (ochtend)	12	0	0%	4	0	0%	12	3	25%	€ 40,29	2	€ 1,48
2-8-2017	10	0	0%	10	1	10%	7	1	14%	€ 40,29	2	€ 5,28
1-8-2017	8	0	0%	9	0	0%	15	3	20%	€ 40,29	2	€ 5,28
31-7-2017	3	0	0%	1	0	0%	8	5	63%	€ 37,07	2	€ 0,01
30-7-2017	5	0	0%	8	1	13%	9	2	22%	€ 37,07	2	€ 0,70
29-7-2017	4	1	25%	5	2	40%	4	1	25%	€ 38,18	1	€ -0,00
28-7-2017	8	0	0%	1	0	0%	8	2	25%	€ 38,18	1	€ -0,00
27-7-2017	9	0	0%	11	2	18%	6	1	17%	€ 38,18	2	€ 2,04
26-7-2017	4	0	0%	5	0	0%	13	0	0%	€ 40,29	2	€ 4,59
25-7-2017	3	0	0%	11	1	9%	10	0	0%	€ 40,29	2	€ 4,59
24-7-2017	5	0	0%	7	1	14%	10	3	30%	€ 39,63	2	€ 3,79
23-7-2017	10	0	0%	6	0	0%	3	0	0%	€ 39,63	2	€ 3,79
22-7-2017	4	0	0%	5	1	20%	3	0	0%	€ 39,63	2	€ 3,79
21-7-2017	6	0	0%	13	0	0%	4	3	75%	€ 39,63	2	€ 3,79
20-7-2017	3	0	0%	5	0	0%	3	1	33%	€ 35,91	1	€ -0,71
19-7-2017	7	0	0%	5	1	20%	5	0	0%	€ 36,98	2	€ 0,59
18-7-2017	6	0	0%	12	3	25%	5	1	20%	€ 36,98	2	€ 0,59
17-7-2017	10	0	0%	3	3	100%	8	2	25%	€ 36,98	2	€ 0,59
16-7-2017	10	0	0%	12	2	17%	9	1	11%	€ 38,80	2	€ 2,79
15-7-2017	10	0	0%	12	3	25%	0	0	0%	€ 36,98	2	€ 0,59
14-7-2017	12	1	8%	1	0	0%	6	1	17%	€ 36,98	2	€ 0,59
13-7-2017	2	0	0%	9	1	11%	5	0	0%	€ 36,98	2	€ 0,59
12-7-2017	13	1	8%	9	1	11%	9	0	0%	€ 35,12	1	€ -1,66
11-7-2017	16	0	0%	12	2	17%	13	2	15%	€ 38,80	2	€ 2,79

10-7-2017	7	0	0%	16	0	0%	10	1	10%	€ 36,32	1	€ -0,21
9-7-2017	14	1	7%	9	1	11%	3	1	33%	€ 38,80	2	€ 4,86
8-7-2017	12	0	0%	8	0	0%	4	2	50%	€ 38,80	2	€ 4,86
7-7-2017	4	0	0%	3	3	100%	4	0	0%	€ 38,80	2	€ 4,86
6-7-2017	13	0	0%	2	0	0%	8	0	0%	€ 38,80	2	€ 4,86
5-7-2017	6	0	0%	4	0	0%	10	3	30%	€ 38,80	2	€ 4,86
4-7-2017	7	1	14%	6	0	0%	10	1	10%	€ 38,80	2	€ 4,86
3-7-2017	7	0	0%	8	0	0%	10	0	0%	€ 38,80	2	€ 3,48
2-7-2017	12	0	0%	3	0	0%	7	1	14%	€ 38,80	2	€ 3,48
1-7-2017	14	0	0%	5	0	0%	6	1	17%	€ 38,80	2	€ 3,48
	Vergelijk.nl: 2% conversie			Tweakers: 15% conversie			Adwords: 17% conversie					

Table 11 Measurement-results from Experiment 1

When checking reliability of the data, a lot of paid clicks from vergelijk.nl could be found on search engines. For example; see image below. The ip-range 66.49.xxx.xxx is an IP-Range owned by google. *Please note; ip addresses are removed from our databases after the execution of the experiment due to privacy laws in the Netherlands.*

id	ip	customer_id	url	referer	date_added ▲ 1	action
3277928	66.249.88.128	0	https://licentie2go.com/beveiliging/totaal-beveili...	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-07-08 02:43:24	BROWSING
3278753	66.249.88.158	0	https://licentie2go.com/Backup-Repair/virtualisati...	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-07-08 05:31:59	BROWSING
3330019	66.249.88.159	0	https://licentie2go.com/beveiliging/totaal-beveili...	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-07-12 06:36:45	BROWSING
3360419	66.249.88.62	0	https://licentie2go.com/beveiliging/totaal-beveili...	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-07-14 08:42:10	BROWSING
3369063	66.249.88.62	0	https://licentie2go.com/Microsoft-Office-365-Enter...	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-07-14 23:02:08	BROWSING
3371460	66.249.88.158	0	https://licentie2go.com/Backup-Repair/virtualisati...	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-07-15 05:30:13	BROWSING
3373767	66.249.88.159	0	https://licentie2go.com/beveiliging/totaal-beveili...	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-07-15 09:42:17	BROWSING
3382549	66.249.88.159	0	https://licentie2go.com/Microsoft-Office-365-Enter...	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-07-16 00:02:05	BROWSING
3383085	66.249.88.158	0	https://licentie2go.com/microsoft-licenties/micros...	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-07-16 01:29:30	BROWSING
3387368	66.249.88.158	0	https://licentie2go.com/beveiliging/totaal-beveili...	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-07-16 10:50:48	BROWSING
3406639	66.249.88.63	0	https://licentie2go.com/Backup-Repair/Backup?mfp=m...	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-07-18 01:54:02	BROWSING
3830057	66.249.88.52	0	https://licentie2go.com/adobe-licenties/adobe-ligh...	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-07-18 02:49:29	BROWSING
3407427	66.249.88.62	0	https://licentie2go.com/office-365-office-2016	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-07-18 04:13:12	BROWSING
3421589	66.249.88.63	0	https://licentie2go.com/office-365-office-2016	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-07-19 06:13:24	BROWSING
3481558	66.249.88.62	0	https://licentie2go.com/microsoft-licenties/Office...	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-07-24 06:31:50	BROWSING
3598978	66.249.88.54	0	https://licentie2go.com/adobe-licenties/adobe-ligh...	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-08-03 13:46:35	BROWSING
3616555	66.249.88.52	0	https://licentie2go.com/microsoft-licenties/micros...	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-08-04 12:33:03	BROWSING
3628965	66.249.88.53	0	https://licentie2go.com/adobe-licenties/adobe-ligh...	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-08-05 04:19:00	BROWSING
3253231	66.249.88.128	0	https://licentie2go.com/Backup-Repair/virtualisati...	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-08-06 03:25:39	BROWSING
3685608	66.249.88.53	0	https://licentie2go.com/microsoft-licenties/micros...	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-08-08 03:41:48	BROWSING
3288992	66.249.88.61	0	https://licentie2go.com/beveiliging/totaal-beveili...	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-08-09 03:39:44	BROWSING
3301041	66.249.88.63	0	https://licentie2go.com/Microsoft-Office-365-Enter...	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-08-10 03:00:59	BROWSING
3371090	66.249.88.61	0	https://licentie2go.com/Microsoft-Office-365-Home-...	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-08-15 04:34:11	BROWSING
3795761	66.249.76.32	0	https://www.licentie2go.be/index.php?route=product...	https://www.licentie2go.be/ESET?product_id=2443&am...	2017-08-15 17:26:20	BROWSING
3384271	66.249.88.159	0	https://licentie2go.com/Microsoft-Office-365-Home-...	https://www.google.nl/url?sa=t&rct=j&q=&am...	2017-08-16 04:35:32	BROWSING

Figure 18. Clicks from Google paid to Vergelijk.nl

Data Gathered in Experiment 2

The table below shows an overview of the database-records for measurements performed in Experiment 2. Important to note in this overview are a number of things:

1. The request URL. An example url is: https://licentie2go.com/filename.php&trgt=cHJpY2U9NjguNzU7cHRoPU1pY3Jvc29mdC1PZmZpY2UtMzY1LUhvbWUtUHJlbWl1bTs=&odest=Microsoft-Office-365-Home-Premium&tracking=55dABCTESTb20ed&prod_datalink_id=123456
    a. **Odest variable**. This variable shows the original destination requested by the user. This destination can be linked back to a product, an information page or any other location on our website. In the example above, the original destination was: Microsoft-Office-365-Home-Premium
    b. **Tracking variable**. This tracking refers back to our internal referral system. Our webshop measures the referral rate for every linked (known) platform on our shop. For example, the tracking variable in the example might link back to the Tweakers pricebot: 55dABCTESTb20ed
    c. **prod_datalink_id variable**. This variable links back to a unique product ID in our system. When there is a product page requested, this number is an extra validation to find the product, besides the odest variable. In our example url, this number is: 123456
    d. **trgt checksum variable**. This variable is added to the URL to make sure that no modifications in the URL are made. For example, when bots change the URLs or variables in the URLs measurements might be influenced by an external factor. This needs to be prevented. In our example the checksum is: cHJpY2U9NjguNzU7cHRoPU1pY3Jvc29mdC1PZmZpY2UtMzY1LUhvbWUtUHJlbWl1bTs. Please note; the checksum is only available when the URL is from one of our feed providers. There is no checksum when a link is clicked for example in the natural search results on Google.
2. When the link is clicked from a pricebot, we are able to send additional information in our target. This information cannot be seen by the user because it is encrypted. Information is saved as “target” in our database. Example: price=79.95;pth=Adobe-Premiere-Elements-Engels;
    a. **Pth variable**. Can be compared to, and should match with, **odest variable** (see explanation above).
    b. **Price variable**. Reading the price from this URL we know with 100% certainty the price that was shown on the pricebot. Every pricebot is reading price from the website based on an XML feed. Using a system link this, we can make sure to detect all price differences on our website compared to prices shown on the pricebot. When a pricebot is slowly changing prices on the platform, we can make sure (using this system) to chare the price shown in the pricebot to the user.

Table 12. Overview of database with data gathered in Experiment 2

visit_id	visitor_id	visitor_ip	date_added 1	platform_id Linked to oc_affiliate.affiliate_id	target	request_url	url	url_price	costs
13385	1	66 .96	2017-10-10 00:08:50	15	price=68.75;pth=Microsoft-Office-365-Home-Premium;	https://licentie2go.com/index.php?route=portal/red...	https://licentie2go.com/Microsoft-Office-365-Home-...	68.75	0.5000
13386	32928	80 12	2017-10-10 00:14:34	6	price=88.90;pth=windows-10-home-OEM;	https://licentie2go.com/index.php?route=portal/red...	https://licentie2go.com/windows-10-home-OEM	88.90	0.5000
13387	32929	78	2017-10-10 00:15:03	15	price=68.75;pth=Microsoft-Office-365-Home-Premium;	https://licentie2go.com/index.php?route=portal/red...	https://licentie2go.com/Microsoft-Office-365-Home-...	68.75	0.5000
13388	32930	14 35.247	2017-10-10 00:17:07	5	price=19.95;pth=McAfee-Antivirus-1PC;	https://licentie2go.com/index.php?route=portal/red...	https://licentie2go.com/McAfee-Antivirus-1PC	19.95	0.5000
13389	32947	62 .142	2017-10-10 00:31:45	6	price=47.14;pth=Microsoft-Office-365-Personal;	https://licentie2go.com/index.php?route=portal/red...	https://licentie2go.com/Microsoft-Office-365-Perso...	47.14	0.5000
13390	1	66 .127	2017-10-10 00:38:01	15	price=34.95;pth=Bitdefender-Internet-Security--3PC...	https://licentie2go.com/index.php?route=portal/red...	https://licentie2go.com/Bitdefender-Internet-Secur...	34.95	0.5000
13391	32962	21 4.133	2017-10-10 00:46:10	7	price=79.95;pth=Adobe-Photoshop-Elements-15-Window...	https://licentie2go.com/index.php?route=portal/red...	https://licentie2go.com/Adobe-Photoshop-Elements-1...	79.95	0.5000
13392	32962	21 4.133	2017-10-10 00:46:40	7	price=79.95;pth=Adobe-Photoshop-Elements-15-Window...	https://licentie2go.com/index.php?route=portal/red...	https://licentie2go.com/Adobe-Photoshop-Elements-1...	79.95	0.5000
13393	32962	21 4.133	2017-10-10 00:50:00	7	price=79.95;pth=Adobe-Photoshop-Elements-15-Window...	https://licentie2go.com/index.php?route=portal/red...	https://licentie2go.com/Adobe-Photoshop-Elements-1...	79.95	0.5000
13394	32963	13 4.253	2017-10-10 00:51:19	6	price=124.75;pth=adobe-lightroom-6;	https://licentie2go.com/index.php?route=portal/red...	https://licentie2go.com/adobe-lightroom-6	124.75	0.5000
13395	1	66 .127	2017-10-10 00:51:37	15	price=79.95;pth=Adobe-Premiere-Elements-Engels;	https://licentie2go.com/index.php?route=portal/red...	https://licentie2go.com/Adobe-Premiere-Elements-En...	79.95	0.5000
13396	1	66 .127	2017-10-10 00:56:18	15	price=47.75;pth=Microsoft-Office-365-Personal;	https://licentie2go.com/index.php?route=portal/red...	https://licentie2go.com/Microsoft-Office-365-Perso...	47.75	0.5000
13397	1	66 .127	2017-10-10 01:12:00	15	price=46.25;pth=Microsoft-Office-365-Personal;	https://licentie2go.com/index.php?route=portal/red...	https://licentie2go.com/Microsoft-Office-365-Perso...	46.25	0.5000
13398	1	66 .8	2017-10-10 01:42:59	7	price=335.90;pth=Microsoft-Visio-Standard-2016;	https://licentie2go.com/index.php?route=portal/red...	https://licentie2go.com/Microsoft-Visio-Standard-2...	335.90	0.5000
13399	1	66 .8	2017-10-10 01:43:00	7	price=335.90;pth=Microsoft-Visio-Standard-2016;	https://licentie2go.com/index.php?route=portal/red...	https://licentie2go.com/Microsoft-Visio-Standard-2...	335.90	0.5000
13400	1	66 .96	2017-10-10 01:43:01	7	price=335.90;pth=Microsoft-Visio-Standard-2016;	https://licentie2go.com/index.php?route=portal/red...	https://licentie2go.com/Microsoft-Visio-Standard-2...	335.90	0.5000
13401	1	66 .127	2017-10-10 01:43:03	7	price=335.90;pth=Microsoft-Visio-Standard-2016;	https://licentie2go.com/index.php?route=portal/red...	https://licentie2go.com/Microsoft-Visio-Standard-2...	335.90	0.5000
13402	32982	31 .34	2017-10-10 01:49:13	6	price=127.95;pth=Microsoft-Office-2016-Thuisgebrui...	https://licentie2go.com/index.php?route=portal/red...	https://licentie2go.com/Microsoft-Office-2016-Thui...	127.95	0.5000
13403	1	66 .127	2017-10-10 01:52:05	15	price=37.95;pth=McAfee-Total-Protection-onbeperkt-...	https://licentie2go.com/index.php?route=portal/red...	https://licentie2go.com/McAfee-Total-Protection-on...	37.95	0.5000
13404	32983	94 7.189	2017-10-10 01:52:36	15	price=47.14;pth=Microsoft-Office-365-Personal;	https://licentie2go.com/index.php?route=portal/red...	https://licentie2go.com/Microsoft-Office-365-Perso...	47.14	0.5000

IP addresses are partly removed because of privacy protection of customers.

Appendix B; Organisation set-up

9.4 About 2GO Software BV

The business which is subject of my graduation project is 2GO Software BV. Once back in 2014 it was a lovely idea to distribute software digital (as download) instead of software being sold in boxes in physical retail stores. 2GO Software started with an idea of starting a single web-shop selling products, but is now focussing on the software itself. Different shops are being used as a tool to sell the software.

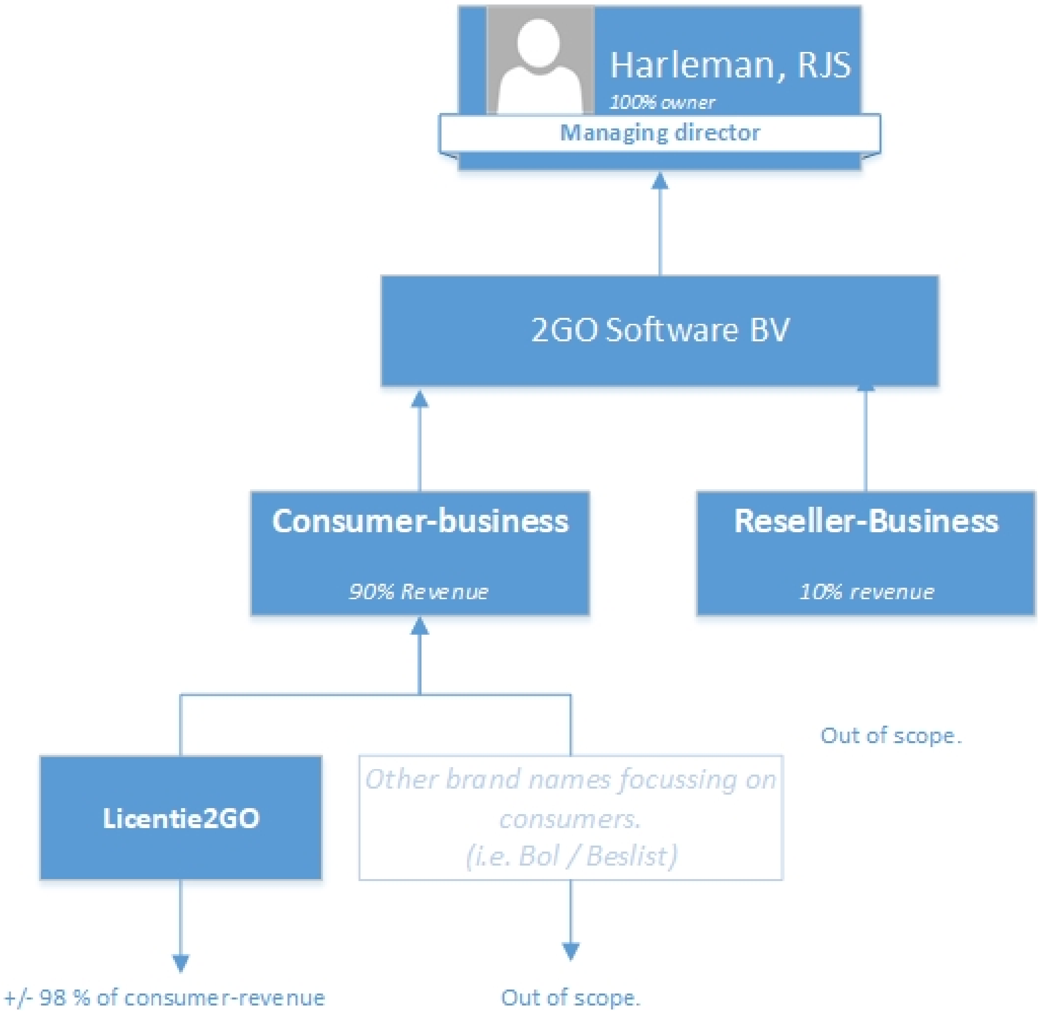

Figure 19. Business Lay-out 2GO Software / Licentie2GO

The structure of the business is shown in Figure 19. The business is owned and run by 1 director: Harleman (author of this document). The business 2GO Software BV is functioning as an umbrella for different brand names. Besides Licentie2GO as a brand name in the consumer-business, other brand names are under development. Other brands are selling equal software, but servicing other customer groups.

9.5 Licentie2GO

Licentie2GO is the oldest brand name of the company. Licentie2GO is a web-shop for end consumers. Using an aggressive pricing strategy, the business is growing rapidly. Licentie2GO was launched in September 2014. Today, at the final stage of this research project (March

2018), the number of customers grew to about 71.500 with a number of orders around 127.500.

9.6 Reseller-Business servicing IT-Professionals

Software-Reseller is the second brand name launched in Q4 2016 in focussing on reseller-clients (mainly IT-professionals and IT-Retail stores). This brand is focussing on resellers-only. The prices of this platform are dynamic and only visible for customers (when logged in). Software-Reseller is competing against large distributors and retail businesses competing in the global and national (digital) retail market. Target customers are computer (physical retail) stores, ICT service companies, ICT professionals, Web-shops selling software, web-shop selling hardware willing to upsell our software products etc.

9.7 Other brand names

Multiple other brand names are under development. Developing new brands opens new opportunities to compete on different advertisement platforms on the Internet. Because of the growth in the consumer market depends heavily on price competition to attract new customers, multiple brand names can help achieve maximum profits in order to survive and offer a competitive price for each product sold. Multiple products are sold with a loss to attract a maximum amount of new customers. More about competition and growth in section 2.1; Environment exploration.

Appendix C: Wall of Entry V1 – source code

Because of the complexity of the source code of the wall of entry and because the source code is commercially sensitive information, parts of the source code can be found below. The source code is for reference purposes only. The technical working of the code is explained in high-level overview in section 5.5.

```php
<?php

/*
 * @project Licentie2GO
 * @file    visit.php
 * @version 1.0.0
 * @created 04-09-2017 11:35:54
 */

class Visit {

    public $session;
    private $cookie;
    private $platform_id;
    private $remote_ip;
    private $accept_header;
    private $user_agent;
    private $costs;
    private $url_price;
    private $target;
    public $request;
    public $db;
    public $visitor_id;

    function __construct($session, $request, $db) {
        $this->session = $session;
        $this->request = $request;

        $this->cookie = (isset($this->request->cookie) ? $this->request->cookie : null);
        $this->platform_id = null;
        $this->remote_ip = (isset($this->request->server['REMOTE_ADDR']) ? $this->request->server['REMOTE_ADDR'] : NULL);
        $this->accept_header = (isset($this->request->server['HTTP_ACCEPT']) ? $this->request->server['HTTP_ACCEPT'] : 'NONE_FOUND');
        $this->user_agent = (isset($this->request->server['HTTP_USER_AGENT']) ? $this->request->server['HTTP_USER_AGENT'] : 'NONE_FOUND');
        $this->costs = 0.50;
        $this->url_price = NULL;
        $this->target = NULL;
        $this->db = $db;
        $this->visitor_id = (isset($this->session->data['visitor_id']) ? $this->session->data['visitor_id'] : 0);
    }

    function addVisitor() {
        if ($this->visitor_id == 0 || $this->visitorExists() == false) {
            if (!empty($this->accept_header) && !empty($this->user_agent)) {
                if (strpos($this->user_agent, 'bingbot') || strpos($this->user_agent, 'Yahoo') || strpos($this->user_agent, 'UptimeRobot') || strpos($this->user_agent, 'Googlebot') || strpos($this->user_agent, 'AhrefsBot') || strpos($this->user_agent,
                'libcurl')) {
                    $this->visitor_id = $this->getOldVisitor();
                } else {
                    $this->db->query("INSERT INTO `visitors` (`accept_header`,`user_agent`) VALUES ('" . $this->db->escape($this->accept_header) . "','" . $this->db->escape($this->user_agent) . "')");
                    $this->visitor_id = $this->db->getLastId();

                }
            }
        }
        return $this->visitor_id;
    }
```

```php
    function addVisitor() {
        if ($this->visitor_id == 0 || $this->visitorExists() == false) {
            if (!empty($this->accept_header) && !empty($this->user_agent)) {
                if (strpos($this->user_agent, 'bingbot') || strpos($this->user_agent, 'Yahoo') || strpos($this->user_agent, 'UptimeRobot') || strpos($this->user_agent, 'Googlebot') || strpos($this->user_agent, 'AhrefsBot') || strpos($this->user_agent,
                'libcurl')) {
                    $this->visitor_id = $this->getOldVisitor();
                } else {
                    $this->db->query("INSERT INTO `visitors` (`accept_header`,`user_agent`) VALUES ('" . $this->db->escape($this->accept_header) . "','" . $this->db->escape($this->user_agent) . "')");
                    $this->visitor_id = $this->db->getLastId();

                }
            }
        }
        return $this->visitor_id;
    }

    function addVisit() {
        $origin_url = $this->getOrigin();
        $redirect_url = $this->getTarget();
        $this->platform_id = $this->getAffiliate();
        $this->insertVisit($origin_url, $redirect_url);
        return $redirect_url;
    }

    function visitorExists(){
        if ($this->visitor_id > 0) {
            $r = $this->db->query("SELECT * FROM `visitors` WHERE `visitor_id` = '" . (int) $this->visitor_id . "'");
            if ($r->num_rows > 0) {
                return $r->row;
            }
        }
        return false;
    }

    function getAffiliate() {
        $affiliate = null;
        $code = $this->getTracking();
        if (!empty($code)) {
            $r = $this->db->query("SELECT `affiliate_id` FROM `oc_affiliate` WHERE `code` = '" . $this->db->escape($code) . "'");
        }
        if (isset($r)) {
            if ($r->num_rows == 1) {
                $affiliate = $r->row['affiliate_id'];
            }
        }
        return $affiliate;
    }
?>
```