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The Effects of User Tracking and Behavioral Management on Online Prices: A Theoretical Approach

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Abstract:

Purpose: *Only little is known about the technical aspect of dynamic, individual prices in various forms of online-shops as well as how exactly these prices are calculated. The aim of this article is to unveil the variables and patterns behind online dynamic pricing.*
Design/Methodology/Approach: *A Software was witten to gather the necessary database in both, an experimental and non-experimental setting. In addion a statistical regression analysis was conducted to ensure data integrity, by reducing amplitudes and noise from the databasis.*
Findings: *There is vast literature on the topic. Literature is outdated pretty fast, as technology is moving ahead of science finding. Variables such as the user origin, device type, on-page-behavior and eventual cookies from previous website visits rsp. Ads do matter in the finding of the price. In general it could be said, that prices on mobile devices are more dynamic than on desktop versions. Thus, buying on a mobile can either be way cheaper or way more expensive than on a desktop computer. Looking at the GPS data, speaking about the user origin, data shows that there could be a pattern proven, that "discriminates" some countries (e.g., Western-EU, USA) by favoring others, preferably lower-wage markets such as Eastern Europe (Croatia) or India.*
Practical Implications: *The present results suggest how both, vendor and customer can optimize their setting, the data they share and the behavior they show, to optimize the price given in specific situation or on request level, based upon their individual pricing request.*
Originality/Value: *The present study is one of the first studies in the economical framework that does not just list the variables existing, but also linking them together and scientifically prove patterns, as fast as available / statistical relevance could be given.*

Keywords: *Price discrimination, price differentiation, dynamic pricing, online shopping.*

JEL classification: *C15, M39, Z39*

Paper Type: *Research study.*

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1. Introduction

Only little is known also about the technical aspect of dynamic, individual prices in various forms of online-shops as well as how exactly these prices are calculated. Known is, that parameters such as origin of the consumer, recent on-page behavior or the device type used for online shopping might influence the price. It remains unclear, to which extent prices are influenced by these parameters and how / if they are connected with each other. Usually, also, if parameters focus on one individual aspect, typically overlooking the interplay that might exist between, not allowing for comparisons in regards to the full extent of these factors. The idea of price discrimination is one not only relevant to the perception of the general public, but also strongly discussed within the scientific community (Simon and Fassnacht, 2008; Thouvenin, 2016). Price discrimination therein is discussed as a contrast to standard prices that are equal over situations and customers and as a method to siphon of different levels of willingness-to-pay by customers (Krämer, Kalka, and Ziehe, 2016).

Therein a distinction can be made between dynamic pricing and individual pricing – two distinct approaches that can, however, be used in a combined way, as study shows. The core research question answered therein is, how different approaches towards (online) price discrimination influence the actual pricing, thus basing on a qualitative study by Hindermann (2018). Within an extensive literature review, the researcher was able to identify various criteria of price discrimination, including user-based, location-based, time-based and technical factors.

The present work, aims to foster understanding of price differentiation by providing quantitative results on the influence of various factors on prices in online shops. The focus on quantitative estimations of the various factors seeks to set the present work apart from existing literature in the field. Different branches will be compared in order to understand, whether the same factors have the same effect of whether differences exist.

Therefore, the research question aims to connect the thesis topic with existing research studies / state of literature – such as the research paper by Hindermann (2018) – and to build the foundation, on which the second research question should be addressed:

- Which approaches of user behavioral steering and online price discrimination can be identified?
- How do these approaches influence the user experience and the price given?

The research is being based on a broad overview of the various approaches of behavioral steering and online price discrimination and the concepts related to those practical approaches. General research on consumer’s willingness to pay and on the social scientific aspects of human decision making in purchasing situations (Bettmann, 1986; Petty and Cacioppo, 1986; Zeithaml, 1988), explains the general foundation of price discrimination and the reasons, why approaches such as the ones described seem to work so well for companies in order to maximize their profits. As the state of literature shows, research conculdes that the implementation of various aspects of price individualization varies widely between different branches and platforms.

1.1 Materials and Methods

The main goal behind the research methodology of this paper is to foster understanding, which aspects of price discrimination variables are applied to different products at different vendors. The potential influence factors (variables) are derived from the scientific literature, with the cited research of Hindermann (2018) forming the foundation. In conclusion, the author differentiates between the named different factors, based on which prices can be individualized.

1.2 Big Data

Although the terms big data, data analysis, and predictive analytics are often used interchangeably in everyday life and business interactions, they can indeed be clearly distinguished from one another. However they are related and partly based on one another, they remain three distinct terms (Provost and Fawcett, 2013). The term "big data" refers to the data's availability: Contemporary technology and connections allow – and even need – us to collect massive quantities of data. This data may include both personal data (which is often obtained by social media or consumer data) and business data, such as various parameters of sales effectiveness or sensor data from various devices or computer parts (Chen, Mao, and Liu, 2014).

Although collecting and using this data is not always for the (exclusive) purpose of price discrimination, it cannot be defined as an uncommon occurrence, as Xu, Tang, and Zhou (2020) point out “with the recent rise of information technology, the Federal Trade Commission (FTC) estimates that 99 percent of online businesses collect personal information from individuals”.

Rabl and Jacobsen (2014), who concentrate on data management, also define the volume of data produced today, “it is usually not deposited once but several times – it must be exchanged, pre- and post-processed, loaded and protected, both of which entail a methodical approach”. Data itself therefore, does not equal knowledge. Making these data usable (“extract knowledge”) – by sorting, interpreting, and linking them – is what data science is mostly concerned with (Swan, 2013). This specialty, among others, employs mathematical techniques to assess and classify data in order to make them useful to clinicians and policy makers (Provost and Fawcett, 2013).

Predictive Data Additionally, Provost and Fawcett (2013) conclude that only the act of processing and using data confers importance on the data, “simply gathering and possessing data does, as said, not create value, only the constructive method of interacting with and applying the data within the enterprise does”. If the database is reliable, current and trustworthy ("data integrity"), vendors can even use it, to predict future data – in the sense of the research topic, Predict future prices.

Predictive analytics is a kind of data science application. Although data may be used to evaluate past behaviors and activities or to uncover trends in consumer behaviour, the ability to forecast potential events is deemed extremely valuable. Following a long-held belief in the world of psychology that the greatest predictor of future action is actual behavior (Wernimont and Campbell, 1968), this field seeks to make assumptions about future events by analyzing evidence from the past (or, in the case of real-time analytics, the present) (Shmueli and Koppius, 2011). These inventions – and their interaction – lay the groundwork for digital internet shopping, user navigation, and pricing discrimination. Returning to the finding of Ouellette and Wood (1998) that the greatest indicator of potential activity is past behavior, data science enables practitioners to a mass a diverse set of user-related data. This data – for example, past website activity, socioeconomic details, or general purchasing behavior – can be used to forecast customers' willingness to pay (Fudenberg and Villas-Boas, 2006).

1.3 Experimental- and Non-Experimental Setup

Given the complexity and the big amount of parameters and environmental factors that can potentially influence the pricing, an accordingly complex methodology needs to be chosen. Some authors therefore chose an approach combining both the data of real users and automated accounts they generated for the study, to see how result vary. Using experimental and nonexperimental (observational) approaches seemed to be a promising methodological setup (Sekaran and Bougie, 2016). Experimental designs are typically described to have high internal validity for this reason. However, external validity can in some cases be lower, due to experimental settings usually describing hypothetical situations. Simulated users for the present study are designed with this potential limitation in mind.

By operating this approach, the authors were not only able to identify the general and systematical application of price discrimination, but also discovered different access levels to resellers product portfolio. From special offers only for members, to nudging users into higher priced accommodations by hiding the fact, that a bedroom without the breakfast would have also been available. Personalizing search results are showing a "optimized" price and product range to each individual user. However, the authors conclude, that noise, thus general price variations over time (such as price drop when a competitor product becomes available) also can influence the price variations;independent of how how the user behaves.

1.4 Variables

Hindermann (2018) names user-based aspects, such as recent on-page user behavior, the availability of a user account and information stored within it or the browser cache (cookies, browser history). Technical aspects include the operating system type or the differentiation between mobile and desktop devices. Also, the browser itself can be used as a way of differentiating users. For the purpose of this study, apart from the general distinction between various operating systems (Windows, Mac, Linux for desktop devices; iOS and Android for mobile devices) a distinction between various devices themselves will be made. Location-based price-discrimination will also be analyzed within the work.

Spatial price differentiation occurs when a supplier charges different prices for his product in different regions (e.g., at home and abroad). In doing so, it pursues a strategy as described above (see vertical price differentiation) or tries to squeeze out domestic or foreign competitors from the respective market, for example, with so-called dumping prices.

Apart from geographical factors (Rose and Rahman, 2015) and user-behavior (recent on-page-behavior, see Visser *et al.*, 2014) also other factors such as the device used for initiating thetransaction can play a role within price differentiation, as Hupperich *et al.* (2017) were able to demonstrate.

The authors examined online price discrimination using a virtual machine that was manipulated according to various device type tags, so price discrimination based on Device types could be examined. The authors found that location-based price discrimination existed, but user-based price discrimination was very unlikely and that any price differences were more likely to be due to currency rate fluctuations.

1.5 Research Software

By using software developed by the researcher (a price-observing VPN Service) to simulate those variations described above and different user-locations, which will – in accordance with existing findings on the strong influence of user-location – be one of the core goals of the proposed work, the quantitative comparison of the effect of those factors will be analysed. Following the approach described by Rose and Rahman (2015), simulated users will be in the center of this work. The simulations will be conducted using the software PricingBlocker (pricingblocker.org, 2020), developed by the prime researcher and his team for practical purposes of minimizing the effects of price discrimination. Using this tool, the aforementioned factors will be applied to the products and product groups.

On the vendor side, suppliers seem to make simply better use of their factory plants if they keep the level of demand high during off-peak periods by keeping prices low. This is practised above all in highly seasonal industries, such as travel and recreation, but also by telephone companies. Quantity-based ("quantitative") price differentiation manifests itself in quantity discounts, e.g., in wholesale, or in favourable bundle prices, as currently available in the computer sector.

The huge variety of possible influencing factors is also highlighted by a paper contributed by Williams (2017), that states that for the determination of airfares not only price discrimination plays a role but also the dynamic response of companies to changing demand situations.

2. Practical Research

Technical aspects include the operating system type or the differentiation between mobile and desktop devices. Also, the browser itself can be used as a way of differentiating users. For the purpose of this study, apart from the general distinction between various operating systems (Windows, Mac, Linux for desktop devices; iOS and Android for mobile devices) a distinction between various devices themselves will be made. Location-based price-discrimination will also be analyzed within the work. By using the available software (see below) different user-locations can be simulated, which will – in accordance with existing findings on the strong influence of user-location – be one of the core goals of the proposed work.

Following the approach described by (Rose and Rahman, 2015) simulated users will be in the center of this work. This approach offers two advantages to the researcher. By using simulated users that are created for the sole purpose of the study, a purely experimental paradigm is chosen, that is able to control all relevant variables easily and cannot be influenced by (probably unknown) previous behavior. Experimental designs are typically described to have high internal validity for this reason.

However, external validity can in some cases be lower, due to experimental settings usually describing hypothetical situations. The simulated users for the present study are designed with this potential limitation in mind. The second advantage of this approach lays in the research economy. Given the high number of variables that should be analyzed within this research, a observation-centered (thus based on real-life-observational instead of simulated users) design would imply the need for a very big sample and a huge workload on the participants.

Using regression analysis, the planned research aims to answer the main question, in which way various factors are influencing the pricing of products in different industries. The goal is, to be able to make quantitative statements, in regards to how, and to which extent these factors actually influence prices and whether different platforms and different industries show comparable results, thus indicating the state of implementation of dynamic pricing technology overall.

For the final data collection, two time-frames were assessed using the identical methodological approach. This step was introduced in order to a) showcase whether timing itself can influence prices and b) to assess whether the results found in the first assessment showed to be stable over time. In order to examine the time-based pricing effects, products and services were chosen that were available at both times of data collection. A total of four services had to be excluded from the research, as data was only obtainable at the first time frame. Thus, in order to show only comparable results, these services were excluded from the analysis completely. Products and services were chosen from two different vendors respectively, thus from two product vendors and two service providers.

The researcher aimed to assess products and services stemming from different price ranges. The prices of these products and services varied to different degrees in terms of their price variability across the different variations described.

2.1 Pricing Algorithms Influencing Consumer (Group-) Behavior

The author attributes this particularly to the booking process of consumers. When airlines for example respond to demand shocks using dynamic pricing algorithms, they are able to secure seats for late-arriving consumers, which are then charged high prices. The author concludes that customers can also gain a benefit out of the price timing-on-demand discrimination strategies of some airlines, if they are – either consciously or coincidentally are able to use it for their own advantage.

Knowing this, pricing strategy suppliers can induce consumers to buy more than they actually need to cover their requirements. The resulting increase in profit can be further increased by cost degression due to economies of scale. In the case of personal price differentiation, the supplier sets the price according to the group to which the consumers belong.

This kind of group affiliation can also be based on certain socio-demographic characteristics, such as age (youth or senior tariffs) or occupation (student tariffs). With this type of price differentiation, as already described above (see horizontal price differentiation), the supplier can motivate even groups with a lower willingness to pay to buy his product through targeted pricing and thus realise an increase in profit (Zinnbauer and Bakay, 2001).

2.2 Research Database

For the research, travel and electronics branches were chosen, because – as the state of research shows – already a certain amount of scientific literature on those fields exists, indicating that price discrimination is a branch standard. Therefore, it can be assumed, that it will be an appropriate sample to foster understanding of the interplay of the various factors of price discrimination. Furthermore, both these fields are known to be a) data-driven and b) rapidly changing and evolving ones. The theoretical work of this thesis is to explain the foundation of price discrimination and its practical implementation. Therefore, some of the core (technical) foundations of work in this field can be found in the field of data science.

The availability of data and the predictions based on this data enable practitioners to implement various ways of price discrimination building upon their understanding of customers' willingness to pay in dependence of variables variables (Shiller, 2013). This is also highlighted by the recent work of Xu, Tang and Zhou (2020) who name the application of data science to be one of the major foundations of work in this field.

Within the research, a number of relevant approaches towards price differentiation and discrimination were presented. Individual results on these approaches exist, showcasing at least partially their quantitative effect on prices for customers in certain product groups. However, no valid and reliable comparison of these individual results exist. The present work builds on this research gap and aims to quantify the complex relationship between various ways of price differentiation. As Bonatti and Cisternas (2020) or Huang, Mani, and Wang (2019) argue, typically multiple approaches are used within one sales process. It cannot be assumed, that the price a user sees is only influenced by one way of price differentiation, but rather a set and combination of multiple approaches is used to influence the price a user is presented with.

This is taken into account for the research's methodological approach. A systematic variation of the different ways to influence prices should allow for quantifying the relationship. The goal therein lays to answer research question 2 based on the data obtained from this systematic variations. By doing so it should be possible to quantify the relevance of the individual approaches and to foster understanding of the way they are implemented in general and whether they also influence each other.

"Any system wanting to perform large scale search for price discrimination has to parse product pages, extract he location of the price from web pages, and fan out queries to the same product page from other vantagepoints in order to compare the results." (Mikians, Gyarmati, Erramilli, and Laoutaris, 2013). This approach was also recognized and embraced within the present research. The main goal behind the research methodology of this paper is to foster understanding, which aspects of price discrimination are applied to different products at different vendors.

The potential factors are derived from the scientific literature, with the research of Hindermann (2018) forming the foundation. The author differentiates between different factors, based on which prices can be individualized. Hindermann (2018) names user-based aspects, such as recent on-page user behavior, the availability of a user account and information stored within it or the browser cache (cookies, browser history).

2.3 Location Based (User Origin)

In order to assess the impact of geographical location on price discrimination, the present study simulated users from three different regions: Germany, Croatia, India. This differentiation was conducted following the notion of the distinctively different economic powers of these three regions, with Germany being among the most wealthy, Croatia taking on the position of one of the poorer countries within Europe and India being in general described as an emerging eco omy. The present work therefore builds on results presented by Mikians (2013) who showcase, that “from a first glance it seems that locations in USA and Brazil tend to get lower prices than locations in Europe. Within Europe, Finland stands out as the most expensive location.” (Mikians, 2013).

2.4 Browser / Cache Based

Discriminating prices based on pre-existing on-site (and partially off-site) behavior is enabled by using the browser history or the cache of the according client. Another approach is to use behavior of users logged into a specific system, which for the present work was not addressed. Rather it was differentiated between two different aspects of assessing previous user behavior, it was differentiated between new users – thus ones, who did not visit the sites before the responding session and accordingly also did not have a registered account – and existing users, who visited the websites before using an existing account.

In addition to this initial differentiation between new and existing users, the on-site behavior was assessed as well. This aspect was operationalized by differentiating between users who already searched for the same product or service beforehand (although within the same session) and those who did not conduct the same or a comparable search on the according website b fore. Thus, browser-history and cache-based price differentiation was measures using two su pplementing approaches: new versus existing clients on the one hand, and previous search behavior on the other hand. Both aspects are treated as separate data points for the empirical analysis.

2.5 Operating System Based

The distinction between various operating systems was performed on the foundation of different device types. For the mobile devices phones and tablets, Android and iOS were chosen as dominant operating systems. The market of mobile operating systems is shared mostly between those two systems, with Android as of 2021 (thus the time of data collection) taking on the dominant position. Additional but less well distributes operating systems such as the mobile version of Windows were omitted from the analysis. For the desktop and notebook market the operating systems Windows and macOS were chosen for the present analysis, whereas other emerging operating systems such as Linux or ChromeOS were omitted from the analysis, partially due to their lower market share and to their lesser relevance for the topic, where the comparison also follows Windows and macOS.

For all analyses conducted, the most recent available version (not including beta-versions unavailable for the general public) of the operating systems were used. The question, whether the usage of older versions of operating systems might also be relevant for price discrimination has therefore to be omitted from the present analyses due to the high variability and subsequently high number of possible data points arising from such a comparison.

On the ongoing research, parameters such as Device-Based, Adblocker yes/no will be conducted to contribute to the feasibilty of data based research results.

3. Results

Among the main results are those concerning the first research question and thus, the identification of relevant approaches to behavioral steering and price differentiation and discrimination. A distinction between user-based, technical-based, time-based and geographical-based approaches to price discrimination could be identified, forming the foundation of the further empirical work described beforehand.

A vast amount of research already exists in regards to dynamic pricing, from individual prices to price differentiation. Both the technical aspect and the psychological perception of these approaches are discussed widely within the scientific literature, which will be displayed en detail within the final thesis.

Research, such as the one on the subject of Netflix's recommendation system, shows, that individualization in online businesses is an immensely complex field. It can be based on a wide variety of data that online businesses are able to gather both in regards to the user and to the general market situation itself. Therefore, it can be assumed, that results on the way prices are individualized might show complex relationships dependencies and effects as well. The benefits of dynamic pricing have always been well known in industries such as airlines and hotels - where capacity is fixed at short notice and perishable. In recent years, dynamic pricing has become increasingly common in retail and other industries as well. According to Elmaghraby and Keskinocak (2003) there are three main reasons for this development:

(1) The increased availability of demand data due to the use of the Internet,
(2) the ease of price changes due to new technologies and,
(3) the availability of decision support tools for demand data analysis and dynamic pricing such as google analytics or CRM software like sales force.

With dynamic pricing, the sales price more or less "automatically" adjusts to the current market, customer or reseller situation. The most important variable here is the price, as it is the absolute measurement of the balance between offer and demand. The logic seems to be simple. If the demand for a product increases, the price increases. If demand stagnates, suppliers set new buying impulses e.g., by reducing prices (Kremer *et al.*, 2016). Numerous online retailers carry a wide range of products and compete with other online retailers. Web crawlers, social listening tools and the setting of auto-adjustment triggers help companies to save personnel costs by automatically carrying out price analyses and -adjustments (Hwang and Kim, 2006).

As some of the research articles presented within this publication show, the choice of the sample is of crucial matter for the results, which is also proposed by research methodologists like Sekaran and Bougie (2016) who argue, that there has to be a strong overlap between the research question on the one hand and the sample on the other hand. The sample needs to be appropriate in terms of size and selection criteria to make meaningful statements based on it. As the state of research shows, the implementation of various aspects of price individualization varies widely between different branches and platforms. The research will therefore make appropriate distinctions, based on the branch (travelling and electronics vendors), the specific market (domestic/international) and will chose based on these initial distinctions appropriate products that can be used for the analysis.

The travel and electronics branches were chosen, because – as the state of research shows – already a certain amount of scientific literature on those fields exists, indicating that price discrimination is a branch standard. Therefore, it can be assumed, that it will be an appropriate sample to foster understanding of the interplay of the various factors of price discrimination. Furthermore, both these fields are known to be a) data-driven and b) rapidly changing and evolving ones. Based on a market research (see methodological approach) relevant vendors on the market were to be chosen. The study therefore aims to in each branch analyze various vendors, in order to produce results that can be generalized more easily.

The goal is, to find vendors who offer comparable products, that will form the foundation of the analyses themselves. For each field (travel or electronics) a number of products will be analyzed, in regards of the factors mentioned above. Therefore, vendors have to be chosen that have an overlap of products. The Data analyzed so far showed minimal, maximal and average values accompanied by the standard deviations for the individual products and services that were assessed throughout this study on price discrimination. In order to conduct meaningful analyses, however, products had to be grouped using different approaches.

In a first step, all the products or services of each respective vendor/provider were agglomerated. This step was undertaken to analyze whether individual vendors and providers differ in regards to their price discrimination strategy. This was also computed separately for every point in time and as an overall score combining the two timeframes. When it comes to price determination methods on the other hand, prices are determined by the company itself within a “unit price” and therewith not according to demand, either individually or according to the general or resellers situation.

The literature review conducted throughout this research indicated, that price discrimination strategies seem to be widely applied throughout various industries and the online retail landscape. Individualized pricing is therein described to be based on various factors, with a clustering between device- and user-based approaches being derived. Online price discrimination has as said been examined by a wide number of researchers since a couple of years, thus also making it possible to follow the evolvement of price discrimination technologies on a scientifical level. It should be stated, that technological progress in the field of online price discrimination moves quickly and empirical findings may be outdated soon. So, there is a potential limitation with every literature review concerning this topic.

Device-based approaches (Sears, 2020) are according to the literature analyzed throughout the work enabled by aspects of the device used for online-shopping. Typical differentiations occur between the type of device (mobile/phone, tablet, notebook, PC) or the operating system used (iOS, Android, Windows, Mac). User-based approaches of price discrimination (Bonatti and Cisternas, 2020) focus on prior user behavior and aspects of the user's on-site behavior (both recent and present).

However, this distinction does not seem to imply mutual exclusivity of these two approaches, as combinations of these approaches are used throughout the examples discussed within the analysis. Further aspects of price differentiation are described as a result of market-based developments and are therefore considered to be outside of the scope of this research paper. The results indicate price discrimination effects which in their general structure are similar for different vendors. Final research needs to be utilized to demonstrate the stability of the existing research and the external validity by including quantitative analyses of additional vendors over different timeframes.

Aspects of data privacy and the impact of the GDPR data privacy law within the European Union will influence the research topic further (Borgesius and Poort, 2017).

4. Conclusions

The approach chosen for the empirical work offers two advantages to the researcher. By using simulated users that are created for the sole purpose of the study, a purely experimental paradigm is chosen, that is able to control all relevant variables easily and cannot be influenced by (probably unknown) previous behavior.

So far, no unifying conclusion can be made in regards to the nature of differences, although the statistical analysis employing paired-sample t-tests again confirmed the statistical relevance of the differences identified here: Products were on average and across all vendors significantly cheaper within the second point of time, whereas the opposite is true for services, which increased in price.

The main outcomes of the present work, however, do not stem from these individual comparisons. While they showcase the differences between vendors and thus the stability of results, the main goal of the study was to assess the degree of price discrimination in use across products and vendors.

For this sake, various computations were conducted that allowed for such analyses. The first step of the resulting analysis is to displayed within the following research period. The effects of price discrimination as described will be analyzed for the sector of products. The average was computed above both points in time, thus not assessing the stability of results over time (the according analysis is described within the appendix of this work and within the previous section for an overall comparison of points in time).

As by now, research results show significant main effects for all independent variables used: Prices in Germany, Croatia and India differed significantly from each other ($F(2) = 336.972$, $p < .01$) with the pairwise comparisons also being significant, thus indicating differences between all countries assessed. Prices across different types of devices (tablet, smartphone, notebook/desktop) also differed significantly ($F(1) = 235.489$, $p < .01$), as did those for client type and prior user behavior.

A less clear picture was depicted based on the analysis of potential interactions between these variables. Therein it could be shown, that mostly those interactions, where the location was involved, seemed to be of significance. One of the examples of such a significant interaction is the one between country and device type. Again, it could be shown for the assessment of main differences between the relevant variables in regards to the prices of services, that all main effects are of statistical significance. The most noteworthy interaction effect is the one between countries' operating systems.

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