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Thesis

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The Effects of Privacy Concern on Mobile Advertising Effectiveness

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ABSTRACT

Consumers are becoming more aware and concerned of the privacy risks on the internet. Companies are using consumer's personal information to personalize advertisements. For consumers there is a benefit to this as they only get advertisements that are relevant to them. The cost for this personalization is that companies collect, use and store consumers' private information. Consumers have to make a trade-off between privacy concerns and ad relevance. In this thesis I introduce a new construct for privacy concern, Consumer Privacy Conscientiousness (CPC), which will be used to research the effect of privacy concern on click intention, willingness to share personal information and willingness to pay for privacy regarding smartphones. I used several linear regressions and a few mediation analyses on a dataset with 291 respondents to test these relationships. The results showed that CPC has a significant negative effect on the click intention of personalized ads and also a significant negative effect on the willingness to share personal information. The effect on willingness to share personal information is mediated by value of privacy and value of ad relevance. The results of this thesis can be used by companies to segment consumers and to target mobile advertisements more effectively.

Keywords: Consumer Privacy Conscientiousness; privacy concern; ad relevance; willingness to share personal information; willingness to pay for privacy; privacy calculus theory; theory of reasoned action; expected utility theory.

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1. INTRODUCTION

Mobile advertising gives advertisers the possibility to personalize advertising messages to individual consumers by accessing their personal information such as demographic data and information about their location. The personalized advertisements take consumers' preferences and behaviors into account to tailor the ad and thus making it more valuable to the consumer and therefore possibly more effective (Lambrecht and Tucker 2013). Mobile devices have the advantage over computers and laptops that they are much more personal and not shared among different people. Furthermore ads can be personalized according to the consumer's location and environment, which makes targeting on a mobile phone more precise (Chen and Hsieh 2012). This is a huge benefit but personalizing advertisement takes a lot of knowledge of the personal lives of consumers and may thus raise privacy related questions. In particular consumers are becoming aware that firms gather more personal information about them. There is a growing concern about how companies collect, store and use the private data of their consumers. In the past years consumers' privacy concerns kept growing. This is mainly caused by the use of personal information in ads, the political debates about privacy issues and by the many security breaches at big companies (Anton, Earp & Young, 2009; Goldfarb and Tucker, 2011).

A good example of a security breach is the case of Target. In November 2013 hackers installed a malware in Target's systems and were able to steal more than 40 million credit card numbers, 70 million addresses, phone numbers and other personal information about everyone who had ever made a purchase at Target. When the malware was being installed, Target's newly installed security software sent out a warning to the security center of Target, but no action was taken. Following the incident consumers and banks filed lawsuits against

Target for negligence and their stocks dropped. Their transactions and sales dropped with more than 46% the during the holiday months that followed[1].

A more recent incident involved the user's password database of eBay. This database included names, emails, passwords, addresses, phone numbers, and birth dates. According to the company this database did not include financial information. However, the news led to an immediate fall of the company's shares[2].

Facebook is another company that knows a lot of personal information about their users. In 2014 they got a lot of critique because they manipulated the timeline of their users for research purposes. According to Forbes, Facebook added the word "research" to their privacy policy four months after this news feed manipulation[3]. This means that at the moment of manipulation they invaded the users' privacy without their consent. This is just a recent and well known example of privacy concerns related to Facebook, but there is a lot of backlash related to the way Facebook handles and uses consumer data.

These cases of big companies losing and misusing consumers' personal information make consumers more aware and concerned about their privacy. Consumer groups argue that mobile advertising raises a lot a privacy concern because of the amount of private data collected to personalize advertisements. These groups are afraid that companies will abuse this information if it is not controlled. Already in 2009 two consumer groups (The Center for Digital Democracy and the U.S. Public Interest Research Group) made a petition to the

[1] Riley, M., Elgin, B., Lawrence, D. & Matlack, C. (March 13th 2014) Missed alarms and 40 million stolen credit card numbers: How Target blew it. Retrieved from http://www.businessweek.com/articles/2014-03-13/target-missed-alarms-in-epic-hack-of-credit-card-data

[2] Reisinger, D. (May 21st 2014). Ebay hacked, requests all users change passwords. Retrieved from http://cnet.com/news/ebay-hacked-requests-all-users-change-passwords/

[3] McNeal, G.S. (June 30th 2014). Controversy over Facebook emotional manipulation study grows as timeline becomes more clear. Retrieved from http://www.forbes.com/sites/gregorymcneal/2014/06/30/controversy-over-facebook-emotional-manipulation-study-grows-as-timeline-becomes-more-clear/

Federal Trade Commission asking them to protect consumers[4]. This can of course impact the mobile advertising market immensely.

Researchers, such as, C. Tucker, A. Goldfarb, R.T. Rust, P.K. Kannan and N. Peng, are becoming increasingly aware of this rise in privacy concerns and are beginning to study this privacy dilemma. For instance, Rust, Kannan and Peng (2002) created an economic model to study what happens when privacy can be traded. They found that consumers will have less privacy over time and that privacy will be very expensive in the event that no other factors, such as governmental restrictions, interrupt the market. Goldfarb and Tucker (2011b) researched the impact of privacy regulations in the European Union and found that display advertising was less effective after the implementation of the Privacy Directive.

To find out if the privacy problem is indeed this big and will have an impact on the profitability of mobile advertising it is important to have empirical evidence. In this thesis I will research the effect of privacy concerns on the effectiveness of mobile advertising.

For this thesis it is important to know what falls under mobile marketing. The Mobile Marketing Association has come up with the following definition of Mobile Marketing which is: “Mobile Marketing is a set of practices that enables organizations to communicate and engage with their audience in an interactive and relevant manner through and with any mobile device or network”[5]. According to the Mobile Marketing Association, the engagement can be initiated by the consumer or by the marketer. Engagement initiated by the consumer is called pull and can be in the form of a click or a response.

[4] Consumer groups petition Federal Trad Commission to protect consumers from mobile marketing practices harmful to privacy. (January 13th 2009). Retrieved from http://www.democraticmedia.org/mobile-marketing-harmful

[5] Mobile Marketing definition. Retrieved from http://mmaglobal.com/news/mma-updates-definition-mobile-marketing

Marketers and companies such as Google and Facebook see mobile marketing as the future of marketing. According to a study conducted by mobilemarketing.nl (the Mobile Marketing Monitor 2013), marketers find the interactive possibilities of mobile advertising the biggest advantage followed by the involvement between brand and customer. Other advantages are the use of location based services, the reach and measurability. According to the CFO of Facebook the growth of mobile advertising is clearly visible in the financial results of the company[6].

A 2013 research by mobilemarketing.nl on the top 500 advertisers in the Netherlands (the Mobile Marketing Monitor 2013) showed that 85% of advertisers use mobile marketing. These advertisers were asked which tools of mobile marketing they are using at the moment. Graph A1 in appendix A shows the results for all possible mobile marketing tools, not only advertising. For this thesis I will focus on advertisements that are not placed on a firm's own platforms such as (mobile) websites, branded apps and email marketing but on advertisements on external platforms.

Taking the definition of the MMA and the 2013 research into consideration and excluding the tools on a firm's own platform, mobile marketing can be divided into four main groups; SMS advertising, advertising through the web browser, mobile coupons and advertising inside mobile applications. These four forms of mobile advertising are briefly discussed below.

First, firms may use SMS advertising to reach mobile users. Text messages as advertisement have been used since the beginning of mobile phones but have become outdated since the upcoming of smartphones with internet access. To reach smartphone

[6] Goel, V. (January 29th 2014). Big profit at Facebook as it tilts to mobile. Retrieved from http://www.nytimes.com/2014/01/30/technology/rise-in-mobile-ads-pushes-up-revenue-and-profit-at-facebook.html?_r=1

users as well as feature phone users the best approach is SMS advertising. A study by emarketers.com shows a decrease in SMS marketing of 11% in 2012 and an increase of 3,1% in 2013[7]. In the future an even smaller growth is expected, but Coca-Cola for example has announced that SMS will continue to be an important element in their marketing strategy[8]. JCPenny is also using SMS marketing. To promote their Easter dresses they sent out SMS advertising to consumers who had opted-in for these messages. The message was intended to drive traffic to the stores, but also included a link to the mobile site of the store where consumers could also buy the dresses[9]. This is a good example of how SMS advertising can drive sales.

Second, many firms target smartphone users by advertising through the phone's web browser. Advertising through the mobile web browser occurs on almost the same matter as on the internet on the computer. Marketers can choose to advertise on a mobile version of a website or they can advertise on search engines such as Google. The Hair Club for Men used Google mobile ads to target consumers and direct them to their mobile website. The mobile site was designed and optimized to drive consumers to call and make an appointment. This approach led to a 6% increase in mobile conversions[10].

Third, firms can advertise by sending coupons to mobile phone users. This can be done randomly or can be planned to send a message when the consumer is at a certain location and more prone to buy the product. The latter case makes use of GPS information to obtain the location of the user. A great example of the use of coupons in mobile

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[7] Most digital ad growth now goes to mobile ad desktop growth falters. (December 16th 2013). Retrieved from http://www.emarketer.com/Article/Most-Digital-Ad-Growth-Now-Goes-Mobile-Desktop-Growth-Falters/1010458

[8] Murphy, D. (May 10th 2011). SMS is it. Retrieved from http://mobilemarketingmagazine.com/sms-it/

[9] Kats, R. (April 20th 2014). Top 10 SMS campaigns of Q1. Retrieved from www.mobilemarketer.com/cms/news/messaging/12633.html

[10] Abramovich, G. (January 9th 2014). 5 Mobile ad campaigns that worked. Retrieved from http://digiday.com/brands/5-mobile-ad-campaigns-that-worked

advertising is the app Scoupy. Firms can advertise with coupons using this app. Scoupy has two ways of reaching the consumers. The consumers can open the app and search for an offer or they can opt-in to receive push notifications. The second option is based on the location of the consumer and the preferences they have entered. If they are within 200 meters of a company they chose to follow they will receive a message from the Scoupy app with a discount offer[11].

Fourth and last, firms can choose to advertise inside a mobile application for games or social media. In-app advertising is relatively new compared to web advertising. When advertising inside an app, marketers use graphic advertisements that are shown during the use of a certain app. These are mostly free apps that earn money by showing advertisements. This can be a banner that stays on the screen the whole time you use the app or it can be a pop-up banner that comes up after you have worked in the app for a while. In games that can be for example after you have made a move and your turn is over. These pop-up banners are usually full screen and can only be closed by waiting a few seconds and/or clicking on a skip button. Consumers can click on the advertisement which will then lead them to a specific page. A nice example of a company advertising inside an app is Albert Heijn. They advertised inside the 9292ov travel app to target travelling consumers who were most likely near a AH To Go shop. The advertisements were time-targeted, which meant that consumers would get 3 different offers throughout the day during three time intervals. By advertising inside the 9292ov app Albert Heijn had the possibility to reach the 150.000 active users of that app[12].

[11] Otto, R. (February 6th 2014). Scoupy zet locatiegebonden pushberichten in. Retrieved from http://www.adformatie.nl/artikel/scoupy-zet-locatie-gebonden-pushberichten
[12] Mobile advertising van Albert Heijn op 9292. (August 23rd 2014). Retrieved from http://adfactor.onstuimig.nl/cases/case/mobile-advertising-van-albert-heijn-op-9292

For the purpose of this research the focus will be on advertising inside mobile applications. The reason for this is that advertising in mobile applications is the most used form of mobile advertisement (see graph A1 in appendix A). Therefore, in this thesis whenever I refer to mobile advertisement, I specifically refer to advertisements placed inside mobile applications such as games, social media and other mobile applications. The goal of this master thesis is to examine how the growing privacy concerns impact the effectiveness of mobile advertisements. It is possible that personalized messages won't work when consumers think their privacy was violated by the company (White et al 2008; The New York Times[13]). In this thesis I will also research the willingness to pay for privacy for different types of consumers. To do this I follow Rust et al's (2000) assumption that a market for privacy may emerge in the future. To study the topic of my thesis I formulated the following research question:

"How will a consumer's view on privacy affect the effectiveness of mobile advertisement?"

To be able to answer this research question the following sub-questions have to be answered first.

1. "Does Consumer Privacy Conscientiousness affect consumers' willingness to pay for privacy, their willingness to share personal information and their intention to click on an ad?"

[13] Stone, B. (March 3th 2010) Ads posted on Facebook Strike Some as Off-Key. Retrieved from http://www.nytimes.com/2010/03/04/technology/04facebook.html?_r=1&

2. *"Do consumers' values of privacy and value of ad relevance have a mediating effect on their willingness to pay for privacy, their willingness to share personal information and their intention to click on an ad?"*

3. *"Can consumers' personal characteristics (such as age, gender, income and education) and behavior (the proxies) predict their CPC level?"*

4. *How can Consumer Privacy Conscientiousness be used to segment consumers?*

This thesis contributes to the academic literature in marketing and to the managerial practice in the following ways.

At the moment there is a lack of research on the effect of privacy concerns on the effectiveness of mobile ads. Advertisers spend a lot of money on mobile advertisement. It is important for them to spend this money effectively. Due to new technologies it is possible to target specific consumers with personalized advertising. Different aspects of privacy concerns have been studied in previous researches such as: the effect of targeted ads and obtrusive ads on the effectiveness of online advertising (Goldfarb & Tucker 2011), the emersion of a market for privacy (Rust et al 2002) and the effect of privacy regulations on the effectiveness of online advertising (Goldfarb & Tucker 2011b). However, there aren't any studies on how privacy concerns affect personalized advertising on mobile phones. Therefore, a study on the effect of privacy concerns on the effectiveness of mobile advertising is necessary. In this thesis I will introduce a new construct called Consumer Privacy Conscientiousness. This construct can help companies to segment consumers and optimize targeted advertising.

With the results of this thesis managers and advertisers can spend their budget more effectively. They can use consumers' CPC level to target the right consumers for their advertising campaigns.

The thesis will have the following structure. First the theory and hypotheses will be discussed. Based on this literature review several hypotheses will be formed. Then the research methodology will be discussed and the results will be presented. The final part of the report will have a discussion and conclusion on the results found.

2. THEORY AND HYPOTHESES

The figure below shows the conceptual framework used in this master thesis. I have derived hypotheses for the direct effects of CPC on click intention, willingness to share personal information and willingness to pay for privacy. In order to keep the thesis parsimonious, the mediating effects depicted in figure 1 with the blue arrows, will be explored but not hypothesized.

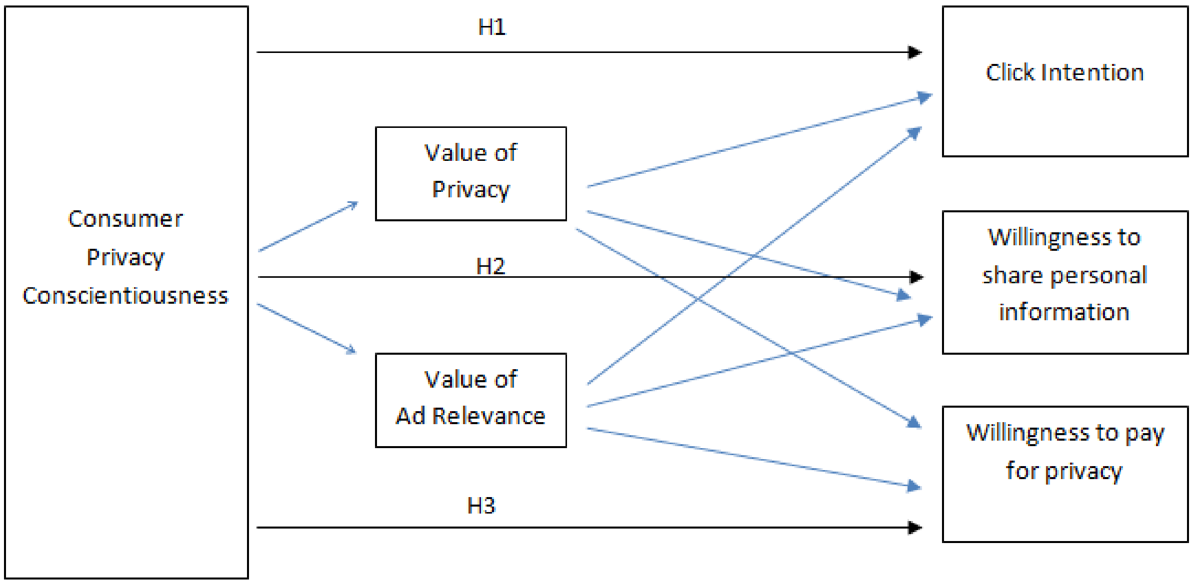


Figure 1: Conceptual framework

2.1. Consumer Privacy Conscientiousness

Personalizing advertisement to a consumer's specific likes and behaviors raises a conflict between the benefits and costs of such ads. Consumers have to decide if and how much privacy they are willing to trade in exchange for ad relevance. In order to advance our understanding regarding the trade-off that consumers need to make between ad relevance and privacy, I introduce a new construct to the literature: *Consumer Privacy Conscientiousness (CPC)*. Conscientiousness is one of the Big Five personality traits. According to Costa et al (1991) people who are conscientious are among other things competent, well organized, logical, foresighted, accomplished, self-disciplined and accurate. According to Costa et al (1991) conscientious people are foresighted, making them more likely to be concerned of the actions of others. This concern for other people's actions makes them also conscientious regarding possible consequences of misuse of their data (Junglas et al 2008). The fact that conscientious consumers are foresighted may also make them more likely to better foresee the consequences of possible privacy breaches making them more concerned about their privacy. In their research Junglas et at (2008) found that the trait conscientiousness has an influence on the concern for privacy of a consumer.

Conscientious people are rational and tend to gather all the necessary information before making a decision. This is also the case regarding the available information about privacy. Conscientious people will therefore be more aware of the risks related to privacy and will be more concerned about their own privacy (Korzaan and Boswell, 2008). Personality traits, such as conscientiousness, can influence the cognitive process of a person and the behavior that corresponds to that process (Li 2012). This means that people with different levels of CPC will behave differently when confronted with privacy issues.

I define *Consumer Privacy Conscientiousness (CPC)* as a consumer trait that determines how concerned a particular consumer tends to be about her or his privacy and how much privacy she or he is willing to trade-off in order to be able to capture more value from firms' offerings. This impacts several areas, such as how much information consumers are willing to give to obtain more customized products and services and also how much privacy they are willing to sacrifice to obtain more personalized and valuable advertising messages. The construct of Consumer Privacy Conscientiousness is becoming more important due to the current trend towards firms' usage of "big data" (often containing individual-level behavioral data) to tailor their offerings and marketing messages. Given these megatrends, I expect CPC to become increasingly recognized as a key individual trait which, in the specific case of 1-to-1 marketing and advertising (the topic covered in this thesis), drives how much each consumer values privacy vs. ad relevance.

Privacy is defined by Rust et al (2002) as the extent to which other people do not know your personal information. Westin (1967, p.7) defined privacy as follows: “the claim of individuals, groups, or institutions to determine for themselves when, how, and to what extent information about them is communicated to others”. For this thesis the definition of Westin will be used.

Westin (1967) used consumer’s attitude towards privacy to divide consumers into three groups. The first and most extreme group consists of the *privacy fundamentalists*. This group of consumers is worried about their privacy rights and breaches of their privacy. This group of consumers is not willing to give out personal information independently of the benefits they can get in terms of ad relevance. The second group consists of *privacy pragmatists*. This group is willing to give out personal information depending on what they can get in return for it. This means that they do a cost-benefit analysis to decide whether or not to give out personal information. The third group, the *privacy unconcerned*, is a group of consumers who are not concerned about privacy and do not mind giving out their personal information for free. Westin has created a privacy index which can be used to divide consumers into the three above mentioned groups. The details about the calculation of this index are not public knowledge and can therefore not be used as a base for this thesis. I have introduced the new concept of CPC that can be used to segment consumers into groups. According to Urban and Hoofnagle (2014), the segmentation of consumers into the groups proposed by Westin (1967) does not have a theoretical basis. Westin uses a more pragmatic approach. The construct of CPC that I introduce in this thesis is based on strong psychological theories, making it a preferred method to Westin's approach.

It is important for companies to be able to recognize the CPC level of a consumer. To that end I examine possible proxies that companies can use to predict a consumer's CPC level without needing to ask them.

2.2. Privacy vs. Ad Relevance Trade-Off: Consequences for Ad Effectiveness, Willingness to Share personal information and Willingness to pay for Privacy

In this thesis I will research the effectiveness of mobile advertising. In order to examine my research questions I focus on a key measure of mobile advertising effectiveness which is click intention. In addition, I focus on willingness to share personal information and willingness to pay for privacy to tap into the trade-off consumers make between privacy and ad relevance. I will rely on well established theories in social psychology – such as theory of reasoned action (Ajzen en Fishbein, 1980) and privacy calculus theory (Laufer and Wolfe, 1977) – and on expected utility theory to develop my hypotheses.

The key success metric for a mobile ad is whether or not consumers click on it. This may be driven by consumer's privacy concerns which can also affect their willingness to share personal information and their willingness to pay for privacy. I will test to what extent CPC predicts the three dependent variables (the click intention, willingness to share personal information, willingness to pay for privacy) which I will now discuss in turn.

2.2.1. Ad Effectiveness: Click intention

There are several ways to measure ad effectiveness, but in the case of mobile advertising it is not always possible to measure sales. Also, some companies have other purposes for their advertisements such as brand awareness or generating traffic. Measuring the amount of clicks of an ad is one possible measure of ad effectiveness. Even though click-ratio's of advertisements are low, clicks measure consumers' behavior and are therefore a better measure than exposure (Chatterjee et al 2003). For the purpose of this thesis, effectiveness will be measured by the intention to click on the advertisement. According to the theory of reasoned action (Ajzen en Fishbein, 1980), intention is a good predictor of behavior. I therefore believe that click intention is a strong predictor of actual clicks. The click intention of consumers will be measured for personalized vs. general ads.

The theory of reasoned action has been used in several researches on information privacy. Building on the theory of reasoned action (Ajzen en Fishbein, 1980) privacy concern, which can be seen as an antecedent belief, can have an effect on a consumer's attitude which can influence the consumer's intention (Sheng et al 2008). According to Xu et al (2005) privacy concerns have a negative effect on behavioral intention. Chellappa and Sin (2005) find that privacy concern has a negative effect on the use of personalized services. Turow et al (2009) conducted a survey and found that 86% of young American adults do not want personalized ads if it means that their behavior on the internet (and offline) is constantly being monitored.

A consumer with a high CPC can react differently to personalized messages than a consumer with a low CPC. Conscientious people react rational and are more aware about privacy issues. This has been confirmed in a study by Junglas et al (2008) on location based services in which they found a significant relationship between conscientiousness and concern for privacy. Bansal (2011) introduced the Internet Users Information Transmission Security Concern (IUITSC) scale which covers privacy and security concerns. He found that there is a positive relationship between conscientiousness and IUITSC.

Personalized advertisements use collected information about consumers to target them. They use personal consumer data or internet behavior data to personalize ads so that it is relevant to the person seeing it. The ads that use internet behavior data, for example, show the exact product that the consumer was looking at just a few minutes or hours before. Consumers are therefore quite aware that their surfing behavior is being monitored and used for advertisements. General advertisements on the other hand are random and do not use any kind of personal information.

Consumers with a high CPC value their privacy very much. Since personalized ads make use of personal information, this goes against the beliefs about privacy of people with a high CPC. This is not the case with general ads. Based on this I have formulated the following hypotheses:

H1a: Consumers with a high level of CPC will be less likely to click on personalized ads than consumers with a low level of CPC.

H1b: Consumers with a high level of CPC will be as likely as consumers with a low CPC to click on general ads.

2.2.2. Willingness to share personal information

According to the privacy calculus theory, introduced by Laufer and Wolfe (1977), a consumer's intention to share information is based on a calculus of behavior and that competing factors are considered in light of the possible outcomes. According to Laufer and Wolfe (1977), there are three important aspects regarding the calculus of behavior. The first is that consumers behave a certain way because they think they can manage the information later on. The second is that consumers may restrain from a certain behavior because they may not be able to manage it in the future. The third and last is that consumers have to take future technological progress in account before acting. This means that consumers make a risk-benefit or a cost-benefit analysis and then decide to share information depending on the outcome (Xu et al, 2010). It is a trade-off between sharing information on the one hand and receiving benefits, such as relevant ads, on the other hand. One of the aspects in the calculus of behavior is the possibility to manage the shared information in the future. Companies can apply this theory to their strategy by allowing consumers to manage the information the company has about them. If consumers are able to change or remove their data at any time, this might lower their privacy concern and affect their willingness to share personal information.

In previous research several risk and benefit factors are used. Personalities such as conscientiousness are one of the factors that raise privacy concerns (Junglas et al, 2008). Researchers of privacy concerns use the privacy calculus theory mostly in combination with other theories such as the expectancy theory of motivation or the expected utility theory (Li 2012). The privacy calculus theory is also used by Dinev and Hart (2006). They find that a high level of privacy concern leads to a lower willingness to share personal information. A consumer who is less concerned about privacy is more willing to share personal information and vice versa. Culnan (1993) concluded that consumers who have a positive attitude toward the use of secondary information are less concerned about their privacy.

Consumers with a high CPC will carefully consider the costs and benefits of sharing personal information. They are however likely to focus on the costs of information sharing because they are well aware of the privacy risks associated. Taking the privacy calculus theory into account, consumers with a high CPC will be less willing to share personal information because the costs will weigh more than the benefits. This leads me to the following hypothesis.

H2: Consumers with high CPC will be less likely to be willing to share personal information, when compared with consumers with low CPC.

2.2.3. Willingness to pay for privacy

Rust et al (2002) conclude that in a free market world there will be a market for privacy where consumers can buy a portion of privacy. Rust et al (2002) use the expected utility theory to model how consumers decide to share personal information. The utility function is a function of shared information as a difference between expected benefits and costs. The equilibrium point determines the amount of information a consumer is willing to share. The expected benefits can be money or personalized information and the expected costs can be privacy concerns or risks (Li 2012). Rust et al (2002) has used the expected utility theory on consumer privacy to study the privacy market. Using this theory they have come up with a utility function in which the consumer can maximize utility based on the amount of privacy purchased. They find that an increase in the desire for privacy leads to an increase in the amount of privacy purchased. Tsai et al (2007) found that consumers prefer to buy from companies with better privacy protection despite having to pay a higher price for their products. Since consumers with a high CPC are more concerned with their privacy, they are more likely to be willing to pay for privacy than consumers with a low CPC. This leads me to the following hypothesis.

H3: Consumers with high CPC will have a higher willingness to pay for privacy than consumers with low CPC.

2.2.4. Mediating Effects

It is important to not only study the effect of CPC on the three dependent variables, but also to research the *behavioral process* through which CPC affects these dependent variables. In order to understand such process, and building upon the privacy calculus theory (Laufer and Wolfe (1977), I will also examine the mediating effects of (i) the value of privacy (as potentially reduced privacy captures a possible cost of ad personalization) and (ii) the value of ad relevance (the possible benefit of ad personalization) on the relationship between CPC and the dependent variables of interest.[14] In other words, the CPC concept itself assumes that consumers are heterogeneous in terms of how much they value privacy versus ad relevance. I expect this heterogeneity to translate into different “privacy calculus” strategies, captured by different valuations of privacy versus relevance which, in turn, explain the effects of CPC on (i) click intention, (ii) willingness to share personal information and (iii) willingness to pay for privacy.

The construct *value of privacy* measures how much a consumer values his or her privacy. A consumer with a high value of privacy would like to keep his private information to himself and not have it known by others. On the other hand a consumer with a low value of privacy will have less of a problem, to have his information known by others.

[14] Because of parsimony I do not hypothesize all the mediating paths, but only describe the behavioral process underlying the hypotheses for the direct effects. These behavioral processes entail mediation paths that could be more formally hypothesized and tested in future research.

Based on this I expect CPC to have a positive effect on the value of privacy which, in turn, I expect to have a negative effect on the willingness to share personal information and a positive effect on the willingness to pay for privacy. I also expect the value of privacy to have a negative effect on the click intention of personalized ads.

Ad relevance is about how relevant an ad is to the person seeing it. Ads can be personalized to consumers' specific interests and behaviors making them more relevant to consumers. Ad relevance can be seen in two ways. The ad is relevant to the website/application that it is placed in or it can be relevant to the person watching the ad. Dynamic retargeting is designed to target potential consumers who viewed a certain product on a website but have not made a purchase and have not revisited the website (Lamrecht, Tucker 2013). For the purpose of this thesis ad relevance will be the relevancy of an ad to the person seeing it. The reason for this is that these kinds of advertisements use more personal information which can raise privacy concerns.

Goldfarb and Tucker (2011) find that an ad that has content that is relevant to the website it is on increases the intention to buy in comparison to ads on websites with general content. Based on this I expect CPC to have a negative effect on the value of ad relevance which, in turn, I expect to have a positive effect on click intention of personalized ads.

According to Nowak and Phelps (1997), consumers are more willing to share personal information when they know what the information will be used for. This can be for example to personalize an advertisement. Chellappa and Sin (2005) find that the value of ad relevance has a positive effect on the willingness to share personal information. A survey[15] conducted by a research firm found that consumers prefer personalization over privacy.

[15] Greenberg, P.A. (January 4th, 2000) E-shoppers choose personalization over privacy. Retrieved from http://www.ecommercetimes.com/story/2131.html#

According to the survey 68% would be willing to share personal information and receive personalized ad in return if there is an option to opt-out. This does not mean that this high percentage of consumers is also willing to share all types of personal information. The kind and amount of information that they are willing to share depends on the amount of personalization they can get in return. Based on previous research I expect the value of ad relevance to have a positive effect on the willingness to share personal information and a negative effect on the willingness to pay for privacy.

2.2.5. Beyond CPC: Other Consumer Characteristics

According to Phelps et al (2000), there are four factors that determine privacy concerns. The first is the type of information requested, the second is the amount of control offered, the third is the potential consequences and benefits offered and the fourth and last is consumer characteristics. For this research I want to use factors that are known to companies without having to ask consumers for additional information and that they can use to predict a consumer's CPC level. In this section I will thus discuss other consumer characteristics, beyond CPC, that I need to control for in my analyses.

A few consumer characteristics will be used as moderator variables and will also be used to research to what extend these characteristics can be used to predict the level of Consumer Privacy Conscientiousness. Sheehan and Hoy (2000) examined privacy concerns across demographics and didn't find any meaningful patterns. On the other hand, Graeff and Harmon (2002) found that privacy concerns vary depending on age, gender and income. It is therefore possible that there could be a pattern when looking at privacy concerns regarding mobile marketing. The four consumer characteristics that will be used are explained more in dept below.

The first consumer characteristic I will look at is age. According to Graeff and Harmon (2002), older consumers feel less comfortable using their credit card to buy something on the internet. The second characteristic is gender. According to Graeff and Harmon (2002), male consumers have less privacy concerns than female consumers. The third characteristic is income. According to Graeff and Harmon (2002), consumers with higher income had the most privacy concerns but were also most comfortable with using their credit card online. The fourth and last characteristic is education. This characteristic was not researched by Graeff and Harmon but it might be interesting to see if it has an effect.

2.3. Overview

Dependent variables	Hypotheses
Click intention	H1a: Consumers with a high level of CPC will be less likely to click on personalized ads than consumers with a low level of CPC H1b: Consumers with a high level of CPC will be as likely as consumers with a low CPC to click on general ads
Willingness to share personal information	H2: Consumers with a high CPC will be less likely to be willing to share personal information when compared with consumers with low CPC
Willingness to pay for privacy	H3: Consumers with high CPC will have a higher willingness to pay for privacy than consumers with a low CPC

Table 1: Overview Hypotheses

3. METHODOLOGY

In this chapter I discuss my study design and explain how I measure the variables needed for my research. I also discuss my data collection method, data description and data analyses.

3.1. Study design

In order to test the hypotheses in this thesis I chose to do a quantitative research and used an online questionnaire to collect the necessary data. The questionnaire had closed ended questions which almost all could be answered by choosing one of the options on a five-point Likert item format. The Likert item answer choices varied depending on the question, but ranged for example from strongly agree to strongly disagree. Several of the questions together, such as the questions about CPC, measure a construct. Table D1 in appendix D provides an overview of the measures and constructs including their sources.

All questions required an answer and the respondents could not continue or finish the questionnaire if they did not answer all questions. I chose for this format to prevent that people would (accidentally) skip questions.

The questionnaire was first tested on 10 respondents to see if there were any issues regarding the questions or answers. It became clear that 2 of the statements about conscientiousness ("I get chores done right away" and "I follow a schedule") led to some confusion. I decided to adapt these 2 statements slightly so that they could not be interpreted in more than one way.

The first five questions in the questionnaire were part of a Likert-scale to determine the CPC level of each respondent. The questions to measure CPC are part of a new scale that I developed. Scale construction is a complicated process with several stages to ensure validity and reliability. Due to time and resource constraints I could not follow all the steps as proposed by Rossiter (2002) and Churchill (1979) to construct these scales. I used a simplified process and incorporated some of their suggestions such as specifying the construct, testing for internal consistency, assessing validity and developing norms to make sure that my measure of CPC is valid and reliable. The questions for the CPC construct were formed based on questions about privacy concerns (Smith et al 1996) and statements about conscientiousness (International Personality Item Pool; Korzaan & Boswell 2008). This combination measures how conscientious people are about privacy. Each question consisted of a statement and answers on a 5-point Likert item format ranging from strongly agree (5) to strongly disagree (1).The answers of each respondent were coded and the average was computed to get their CPC score. Consumers with a CPC score between 1 and 2,99 are considered to have a low CPC and consumers with a score between 3 and 5 have a high CPC. These ranges can be used by firms to segment consumers.

To test the click intention of the respondents regarding mobile ads, I added two vignettes in the questionnaire. Alexander & Becker (1978 p.94) define vignettes as “short descriptions of a person or a social situation which contain precise references to what are thought to be the most important factors in the decision-making or judgment-making processes of respondents”. The respondents were asked to imagine a certain situation before answering the question (Xu et al 2009). In the first situation the respondents were asked to imagine using an app on their mobile phone and seeing the displayed advertisement. This advertisement was for toothpaste and was thus a general ad of a low involvement product. In de second vignette situation the respondents were asked to imagine that they wanted to buy a new Canon camera and had searched for information about Canon camera’s on their mobile phone. The next day while using an app on their phone they see the displayed advertisement. This advertisement was for a specific Canon camera and the ad is relevant to the viewer.

The variable willingness to share personal information was measured by asking how willing the respondents were to share six types of private information (Phelps et al 2000) in an app for mobile phones. The six items were the respondent's name, date of birth, location via GPS, telephone number, email address and payment information. Together these six items measure the construct willingness to share personal information. The willingness could be answered on a 5-point Likert item format ranging from very willing (5) to not willing at all (1). The answers of each respondent were then coded and the average was computed to get their willingness to share personal information. This method is the same as the one used for the variable CPC.

The variable willingness to pay for privacy was measured by asking the respondents how willing they are to pay for privacy in a mobile app. They could answers on a 5-point Likert item format ranging from very willing (5) to not willing at all (1). This approach is very simplistic and accurately measuring willingness to pay is more complicated than this. The ideal approach is to use the BDM method (Becker et al 1964), which uses an experimental approach to measure willingness to pay. The BDM approach which is now widely used by researchers (Ding, 2007) and has several variations is as follows. First, the respondent is asked to say how much he is willing to pay. Second, a random price is drawn. Third, if the price that is drawn is higher than the willingness to pay then the respondent can't make the purchase, but if it is lower or equal the respondent can buy at the drawn price. It is in the respondent's best interest to give his true willingness to pay. This approach however is not feasible given the time constraints of my questionnaire, as it would make it unnecessarily long.

To measure value of privacy the respondents were asked two questions (Smith et al 1996) which together measure the construct value of privacy. The answers ranged from strongly agree (5) to strongly disagree (1). Each answer was coded and then I used the same method as with CPC to compute the average value of privacy. The same approach was used on the value of ad relevance, which was also measured with two questions (Phelps et al 2000).

The questionnaire also included some questions to find proxies that would allow a company to predict a consumers CPC level. These questions were about the respondents' behavior with regards to allowing cookies, deleting cookies and reading privacy policies. The possible answers were about how they behaved. The respondent's answers were coded based on how much caution they took, from taking no caution (1) to taking high caution (6).

To research if consumer characteristics have an effect the on trade-off between privacy and ad relevance and to see if they can be used to predict CPC I have asked a few demographic questions. For the variables income and education I have added "I don't want to answer" as one of the answer options. The reason for this is that not everyone wants to give such personal information. Without this option they might choose another answer at random just so they do not have to give out private information and this would influence the results.

An English version and the Dutch version of the full questionnaire including instructions and vignettes are available in appendix B and C.

3.2. Research Quality

Validity

It is important to do a validity check to see if the empirical measure actually measures the researched concept (Babbie 2007). There are various validity criteria that can be used to do a validity check, each discussed below.

Face validity is used to check if the measures agree with our common agreements and our individual mental images regarding the concept. This means that the test has to look valid. It has nothing to do with adequacy of the test. In the questionnaire the questions appear to measure the variables that I wanted to measure such as privacy concern and ad relevance. Construct validity checks if there is a logical relationship between variables. This means that the relationship between the dependent and the independent variable must be logical. For my thesis I looked at literature and previously done studies to check for a logical relationship. Content validity checks if a measurement contains everything that is included in a concept. In this thesis the most likely variables are researched. These variables were compiled using information from previous literature.

Reliability

It is also important to have a reliable measuring method. This guarantees the quality of the research. For a measuring method to be reliable it has to have the same outcome when repeating to the same object (Babbie 2007).

To ensure the reliability of this questionnaire, the following was done. First, I only asked questions that the respondents would know the answer to. Second, the test-retest method was used. One of the questions was asked twice during the questionnaire to see if the respondents would give the same answer both times. To eliminate the possibility that they would simply remember their answer from the first question, the second question was transformed to a slightly different format. Third, a question was added to check if the respondent actually read the questions and answers and answered them seriously. The question added asked if they could fill in the first answer which was “strongly agree”. If someone had this question wrong there is a good chance that they just answered everything randomly and that the results may not be reliable. Questionnaires in which this question was not answered correctly were carefully studied to see if they could be used of should be excluded. Fourth, I used Cronbach’s Alpha to check the reliability of each scale. Last, I used measures that were proved reliable in previous research. The only exceptions were the constructs, such as CPC, that I developed myself.

3.3. Data collection

The data for the quantitative research was collected by spreading the questionnaire online using Google Forms. To stimulate people to answer the questionnaire, everyone who filled in the questionnaire completely and left their email address had a chance of winning a prize. The winners were drawn randomly.

I distributed the questionnaire via email, Facebook and LinkedIn to my friends, family and colleagues and they helped to spread it out further. De Rooij Fotografie, the sponsor of the prizes for the questionnaires, also sent out an email with a link to the questionnaire to their mailing list. This combined way of spreading the questionnaire made sure that it was representative for the whole population. A translation of the questionnaire to Dutch lowered the chance of Dutch people not fully understanding the questions. To prevent any discrepancies in the data as a result of translation differences, the questionnaire was only distributed in Dutch. As a result the questionnaire was only filled in by Dutch respondents, making the results representative for the Netherlands.

3.4. Data Description

The online questionnaire was filled in by 296 people, 52% female and 48% male. All questions were mandatory which meant that there were no incomplete questionnaires. The questions about income and education had the option “I don’t want to answer” which was filled in by a large group of people. I kept the data for these people in the dataset and treated those answers as missing values.

Quite a few respondents had the quality control question wrong. The question was answered incorrectly by 65 out of the 296 respondents which is almost 22%. The question was added to filter out people who filled in the questionnaire just for the prize and did not actually take the time to read and answer the questions. After the questionnaire was send out I got a lot of feedback that this particular question was very confusing. This could explain the high number of incorrect answers. Due to the high percentage and the feedback I decided to carefully study this group to see if the data should be used. I used the Mann Whitney test to see whether there is a significant difference between the groups (right answer, wrong answer). Based on this test there is no significant difference between the two groups for almost all variables except for two. This means that as a group the respondents with the wrong answer didn’t give answers that differed significantly from the other group. This does not mean that individual respondents from this group aren’t possible outliers, so I decided to further analyze them.

I start to analyze the data by looking at histograms and boxplots of the data. One outlier that jumps out is a reported age of 1994. I make the assumption that someone entered year of birth instead of age and I change it to the corresponding age.

I continue analyzing the data by doing a univariate analysis of the one-scale variables. This analysis shows two more outliers in age. Two respondents gave an age of -1 and 1. The same two respondents also had the control question wrong. Based on this I decided that there is a good chance that they were not serious when filling in the questionnaire. I decided to delete the data for these two respondents.

A few other variables also had outliers. With a likert scale I did not expect there to be so many outliers, but it is possible that these respondents just gave their honest opinion and that this differed from the rest of the respondents. Before making a decision I continued analyzing the data using the Mahalanobis D^2 test to find multivariate outliers. This test pointed out 27 possible outliers. I ran the analyses that I wanted to do with and without these outliers and computed the DFBeta's. Those were < 1 which according to Field (2005) indicates that the outliers do not influence the model that much and can stay in the dataset.

This means that the only outliers I had to worry about were the univariate outliers. To see if the answers for these outliers are legitimate I checked their answer on the control question to decide whether to keep or delete the data. I decided to delete the data for 3 respondents and keep the rest in the dataset. The final dataset consisted of 191 respondents. After deleting the outliers I analyzed the data again using histograms, boxplots and descriptive statistics.

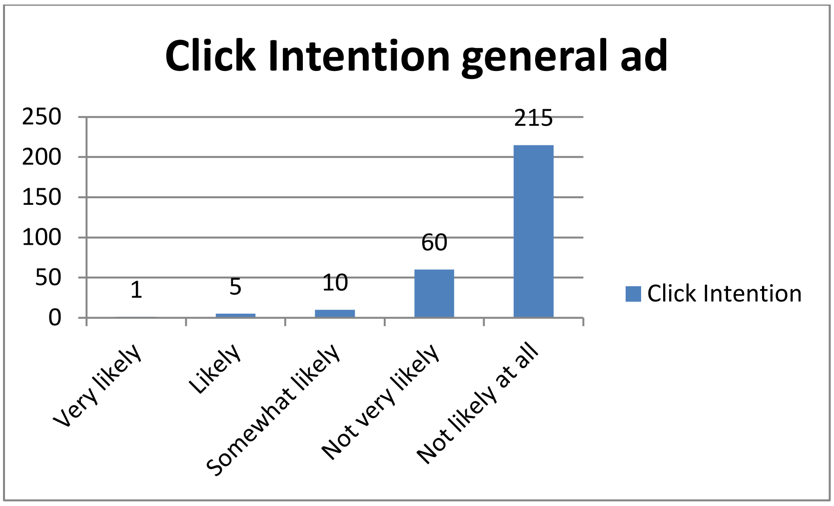
The 291 respondents had an average age of 48,9 years, with the youngest being 16 and the oldest being 80. The average mean of education was 3,4 which means that the average education level was an MBO or bachelor's diploma. The income level was only filled in by 144 respondents and had a mean of 2,4 which means that the average income for these respondents was around 30.000 euro per year. A table with the descriptive statistics of the main variables can be found in table 2. The descriptive statistics of all the other variables can be found in table E1 in appendix E. The definitions of the variables used in SPSS can be found in table E2 in appendix E. A graphical analysis of each of the dependent variables can be found in graphs 1 through 4. The graphical analyses of the other variables can be found in appendix F.

Descriptive Statistics

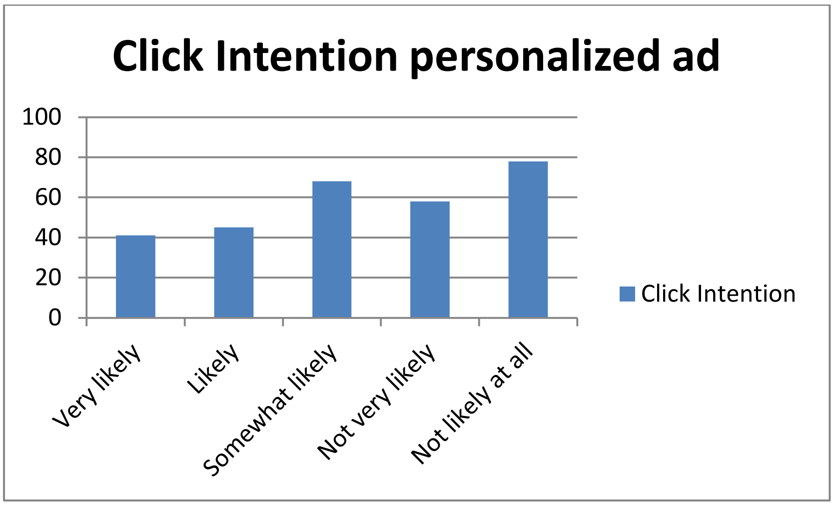
Variable	N	Minimum	Maximum	Mean	Std. Deviation	Number of Items in the construct	Cronbach's Alpha/ Pearson's R[16]
Consumer Privacy Conscientiousness	291	2,40	5,00	4,1292	,55790	5	0,71
Click Intention of a general ad	291	1,00	5,00	1,3402	,66260	-	-
Click Intention of a personalized ad	291	1,00	5,00	2,6942	1,38437	-	-
Willingness to share personal information	291	1,00	5,00	2,2761	,75148	6	0,821
Willingness to pay for privacy	291	1,00	5,00	2,6632	1,22474	-	-
Value of Privacy	291	2,00	5,00	4,3076	,60664	2	0,268
Value of Ad Relevance	291	1,00	5,00	2,7474	,88119	2	0,336
Proxy question 1	291	1,00	6,00	3,4021	1,18024	-	-
Proxy question 2	291	1,00	3,00	1,9485	,87144	-	-
Proxy question 3	291	1,00	4,00	2,9210	,68275	-	-
Proxy question 4	291	1,00	3,00	1,6942	,62637	-	-
Age	291	16,00	80,00	48,9072	14,54582	-	-
Gender	291	1,00	2,00	1,4845	,50062	-	-
Income	144	1,00	5,00	2,4653	1,24549	-	-
Education	253	1,00	6,00	3,4862	1,00633	-	-

Table 2: Descriptive Statistics

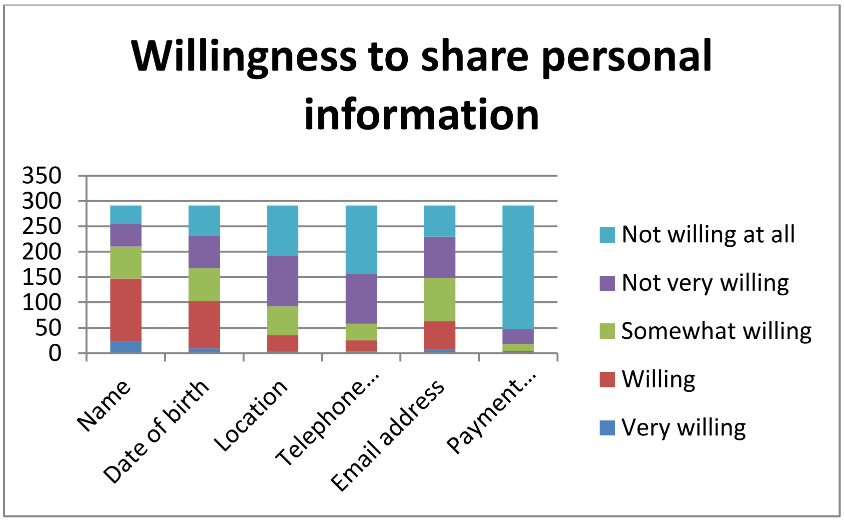
[16] This colomn reports Cronbach's Alpha for the multi-item scales and Pearson's R for the two-item scales.



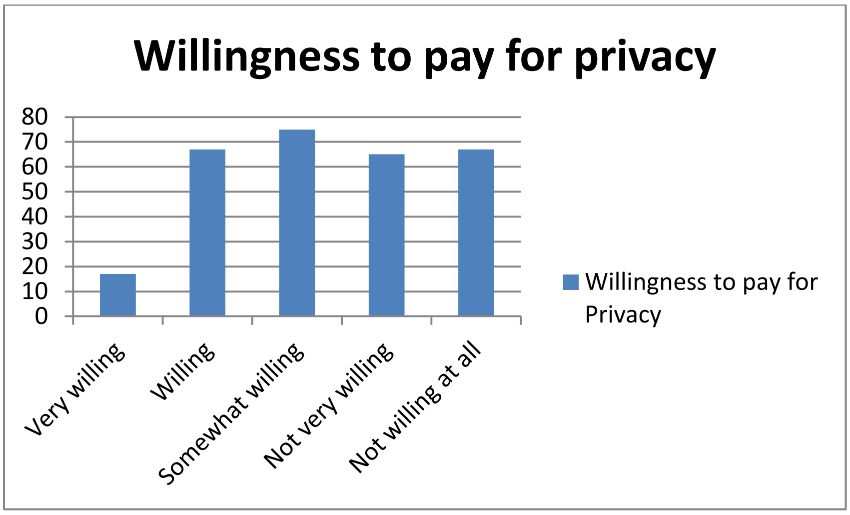
Graph 1: Click Intention of a general ad



Graph 2: Click Intention of a personalized ad



Graph 3: Willingness to share personal information



Graph 4: Willingness to pay for privacy

To test the reliability of the scales used in the questionnaire is used Cronbach's Alpha for the multi-item scales and Pearson's R for the two-item scales. The table with the measured alpha's and Pearson's R's for the scales can be found in table E3 in appendix E. Another table with correlations between all the main variables can be found in appendix G.

Values of .7 and .8 are acceptable levels of alpha. Looking at the results, this means that the constructs for CPC and willingness to share personal information are reliable. The Pearson's R for the two mediating variables is fairly low. This is a bit problematic because it could mean that the two questions do not measure the same thing and this could reduce the statistical power of the scale. However, there is disagreement between researchers about the acceptable level of correlation. Cattel (1965) and Briggs and Cheek (1986) both argue that if the correlation is too high, one of the items on the scale might be redundant because it makes the construct too specific. They find a correlation between .2 and .4 optimal.

To test the reliability of the answers I used the Wilcoxon signed ranks test to test the answers to the question that was asked twice. The test showed no significant difference between the answers of the two questions.

3.5. Data Analyses

I have done several simple regression analyses to test the effect of the independent variable (CPC) on the dependent variables (click intention general ad, click intention relevant ad, willingness to share personal information, willingness to pay for privacy).

To test if value of privacy and value of ad relevance have a significant mediating effect I used the model of Baron and Kenny (1986) which is depicted in figure 2. The X is the independent variable, the M is the mediator variable and the Y is the dependent variable.

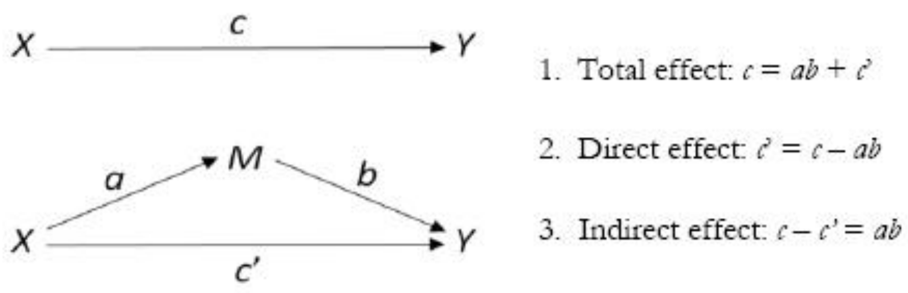


Figure 2: The mediation model

Kenny (2014) discusses four steps that need to be taken in order to test the mediating effect.

1. The independent variable (X) should correlate with the dependent variable (Y)
2. The independent variable (X) should correlate with the mediator (M)
3. The independent variable (X) and the mediator (M) should be used in a regression analysis with the dependent variable (Y)

4. It can only be established that M completely mediates if the effect of X on Y is now zero.

I follow these steps by doing several regression models for each mediating effect. The first step is the simple regression analysis I also used to test the effect of the independent variable (CPC) on the dependent variables.

$$Y = \beta_0 + \beta_1 \times \mathrm{X}$$

The second model is used to test the effect of the independent variable (CPC) on the mediator variable (value of privacy or value of ad relevance).

$$Y = \beta_0 + \beta_1 \times M$$

The final model tests the effect of both the independent variable and the mediator variable on the dependent variables.

$$Y = \beta_0 + \beta_1 \times X + \beta_2 \times M$$

After these steps it is necessary to test if this mediation effect is significant. To do this I used the Sobel test which used this equation:

$$\text{Sobel test} = \frac{a \times b}{\sqrt{b^2 \times \mathrm{S_a}^2 + \mathrm{a}^2 \times \mathrm{S_b}^2}}$$

The test is treated as a z-test which means that absolute values larger than 1.96 are significant at 0.05 and reject the hypothesis that there is no mediation effect.

To test if CPC can be predicted by consumer characteristics I used CPC as a dependent variable and the four consumer characteristics as independent variables. I also wanted to find some proxies that can be used when the CPC level of a consumer is not known. To test if the proxies can predict the consumer's CPC level I ran a regression with CPC as dependent variable and the four proxies as independent variables to see if the consumers' behavior, which was captured in four proxy questions, can predict their CPC level.

I also used the consumer characteristics as moderator variables to test if they influence the effect that CPC has on the dependent variables. This was done by adding interaction effects in the regression model. The equation used was the following:

$$Y_i = \beta_0 + \beta_1 \times X1_i + \beta_2 \times X1_i \times X2_i + \in$$

4. RESULTS

In this chapter I present the results of the regression analyses. I first discuss the effects on each dependent variable followed by the mediating effects. I also discuss the moderating effects of the consumer characteristics and their predictive quality towards CPC. All results have a 95% significance level. The tables with the full results from the analyses can be found in appendix H.

4.1. Direct Effects

The results of the regression analyses conducted can be found in table 3.

	Click Intention Personalized advertisements	Click Intention General advertisements	Willingness to share personal information	Willingness to pay for privacy
β (CPC)	-0.471	0.018	-0.453	0.211
Std. Error	0.143	0.070	0.075	0.129
p	0.001	0.799	0.000	0.101
R squared	0.000	0.036	0.113	0.009
Adjusted R squared	-0.003	0.033	0.110	0.006

Table 3: Regression output

The click intention of the respondents was measured for both general advertisement and personalized advertisement. The regression model testing the effect of Consumer Privacy Conscientiousness on personalized advertisement was significant. The model shows that CPC has a significant negative effect (β= -0.471 and p= 0.001) on the click intention for personalized ads and that consumers with a high CPC level are less likely to click than those with a low CPC level. Based on this H1a is not rejected. I also tested the moderating effect of consumer characteristics on this model. The effects for gender, income and education were not significant. Age had a small but significant positive effect (β= 0.003 and *p*= 0.029). This means that older people are more likely to click on a personalized ad.

The regression model that tested the effect on general advertisements was not significant, based on the F-test (*p*= 0.799). The effect of CPC on the click intention for general ads was also not significant (β= 0.018 and *p*= 0.799). This means that the CPC level has no significant effect on the click intention for general ads, so H1b is not rejected.

To test the effect of CPC on willingness to share personal information another regression model was used. The results showed that this effect was significant. The CPC level of consumers has a significant negative effect on their willingness to share personal information (β= -0.453 and *p*= 0.000) inside a mobile application. This means that a higher CPC level leads to a lower willingness to share personal information. Based on this H2 is not rejected. The consumer characteristics were used to test the moderating effect on this model. Again gender, income and education were not significant. Age once again had a small but significant negative effect (β= -0.002) and *p*= 0.029). This means that older people are less willing to share personal information.

The regression model used to test the willingness to pay for privacy was not significant, based on the F-test (*p*= 0.101). The effect of CPC on the willingness to pay for privacy was also not significant (β= 0.211 and *p*= 0.101). The CPC level has no significant effect on the willingness to pay for privacy. The hypothesis H3 is rejected.

The R^2 and adjusted R^2 for the four models discussed above are also mentioned in table 3. The adjusted R^2 is a measure of goodness of fit and tells how well the model would predict a different sample of the same population. Based on the adjusted R^2 I expect that to be 0.3%, 3.3%, 11% and 0.6%. These numbers are low, which means that there might be some other variables that affect the dependent variables.

The four models were also tested for heteroscedasticity by plotting the residuals. These plots did not show any sign of heteroscedasticity.

4.2. Mediating Effect

The mediating effects of the value of privacy and the value of ad relevance were tested using the methods of Baron and Kenny (1986) in combination with the Sobel test. These mediating effects were only tested on the regression models that had a significant effect to see if this effect was mediated by one of the two mediating variables. Table 4 below shows the input and output of the Sobel test.

	Value of ad relevance on Click Intention	Value of privacy on Willingness to share personal information	Value of ad relevance on Willingness to share personal information
a	-0.267	0.582	-0.267
b	0.234	-0.307	0.177
c	-0.471	-0.453	-0.453
c’	-0.408	-0.274	-0.406
Sa	0.092	0.054	0.092
Sb	0.091	0.078	0.047
Sobel test	-1.925	-3.656	-2.299
p	0.054	0.000	0.022

Table 4: Sobel Test

The Sobel test showed that both value of privacy and value of ad relevance significantly mediate the effect of CPC on willingness to share personal information. The test also showed that the effect of CPC on the click intention of a personalized ad is not significantly mediated by the value of ad relevance. The Sobel test of the mediator value of privacy on the mediating effect of CPC on click intention could not be conducted because the effect of the mediator on the dependent variable was not significant and therefore, there is not indirect effect. This means that only the following two conclusions can be drawn. The first is that CPC has a significant positive effect (β= 0.582) on value of privacy which, in turn, has a significant negative effect (β= -0.307) on willingness to share personal information. The second is that CPC has a significant negative effect (β= -0.267) on value of ad relevance which, in turn, has a significant positive effect (β= 0.177) on willingness to share personal information.

Since the models on the effect of CPC on click intention for general ads and willingness to pay for privacy were not significant there was no need to test the mediating effect of the two mediator variables. I used these mediator variables as independent variables to see if they have a direct effect. The effect of value of relevance was not significant for both dependent variables. The variable value of privacy did not have a significant effect on click intention, but had a significant positive effect (β= 0.278 and *p*= 0.019) on the willingness to pay for privacy.

These models were all tested for heteroscedasticity and none of the models showed any signs of heteroscedasticity.

4.3. Predicting CPC

The four consumer characteristics were not only used as control variables but also to test if they can predict the CPC level of a consumer. The first model used included all four consumer characteristics and gave the output shown in table 5. The goodness of fit of the model is shown in table 6.

	β	Std. Error	*p*
Age	0.011	0.003	0.001
Gender	0.100	0.097	0.308
Income	0.043	0.037	0.255
Education	-0.189	0.045	0.000

Table 5: Regression output

Model	R^2	Adjusted R^2
Consumer Characteristics	0.258	0.236

Table 6: Goodness of Fit

The output shows that age (β= 0.011, *p*= 0.001) and education (β= -0.189, *p*= 0.000) were significant, that gender and income were not significant and that the model had a prediction value of 23.6%. According to the results, age has a positive effect on CPC meaning that older consumers have a higher CPC level. This makes sense because older consumers are less comfortable using the new technologies and are therefore more afraid of the consequences than younger people. Since using new technologies means giving out more personal information, this tends to increase the privacy concern of older consumers. The results also show that consumers with a higher education have a lower level of CPC. It is possible that consumers with a higher education feel confident about the knowledge that they have towards protecting their private information and therefore do not have such high privacy concern in comparison to consumers with lower education. Based on the results I changed the model to only include these two significant variables. This slightly changed the beta's resulting in the following model:

$$CPC\_i = \beta_0 + \beta_1 \times Age\_i + \beta_2 \times Education\_i + \in = 3.843 + 0.013 \times Age\_i - 0.104 \times Education\_i$$

This model can be used to predict a consumers CPC level using the age and income of this consumer. Both models were tested for multicollinearity and heteroscedasticity and showed no signs of either.

I also used the proxy questions to test if they can predict a consumer's CPC level. The proxy questions along with the output of the model with CPC as dependent variable and the four proxies and independent variable are shown in table 7. The goodness of fit of the model is shown in table 8.

	β	Std. Error	*p*
Prox1: How frequently do you delete cookies?	0.082	0.025	0.001
Prox2: Do you make use of the private browsing option in your internet browser?	0.012	0.033	0.714
Prox3: Do you allow websites to place cookies on your computer?	0.225	0.045	0.000
Prox4: Do you read the privacy policies of the websites that you visit?	0.216	0.049	0.000

Table 7: Regression output

Model	R^2	Adjusted R^2
Proxies	0.250	0.239

Table 8: Goodness of Fit

The output showed that prox1 (β= 0.082, *p*= 0.001), prox3 (β= 0.225, *p*= 0.000) and prox4 (β= -0.216, *p*= 0.000) were significant, that prox2 (β= 0.012, *p*= 0.714) was not significant and that the model had a prediction value of 23.9%. The proxy question, which was not significant, was about using the incognito option of the internet browser. A possible explanation is that many consumers are not aware that this option even exists and therefore do not use it. This explains why this proxy question can't be used to predict CPC. The other questions regarding cookies and privacy policy do seem to be able to predict CPC. This means that privacy conscientious consumers take measures to protect their privacy and read privacy policies to be fully aware of all risks involved.

I changed the above mentioned model to only include the three significant variables. This slightly changed the beta's resulting in the following model with a slightly higher R^2 which can be used to predict a consumers CPC level using 3 proxies:

$$CPC\_i = \beta_0 + \beta_1 \times Prox1\_i + \beta_2 \times Prox3\_i \ + \ \beta_3 \times Prox4\_i + \in$$

$$\mathrm{CPC}\_i = 2.821 + 0.084 \times Prox1\_i + 0.224 \times \mathrm{Prox\ 3}\_i \ + 0.217 \times \mathrm{Prox4}\_i$$

These models had multiple independent variables and were tested for both multicollinearity and heteroscedasticity. Multicollinearity was tested using the VIF measure. The output showed values around 1 which means that there is no multicollinearity. There was also no sign of heteroscedasticity.

5. DISCUSSION

In this chapter I discuss the results of the research that are described in the previous chapters.

The click intention of a mobile ad was measured for both personalized and general ads. The analyses conducted on the data showed that CPC only had a significant effect on the click intention of personalized ads. The results show that CPC has a negative effect which means that consumers with a higher CPC are less likely to click on a personalized ad than consumer with a low CPC. This is in line with H1a and with the findings of Xu et al (2005) that privacy concerns will negatively affect behavior. The effect on click intention is negatively moderated by age and is thus strengthened when the age of a consumer goes up. The effect of CPC on click intention for personalized ads was also tested for mediating effects, but these effects were not significant. The effect of CPC on click intention for general ads was also not significant. This is in line with the hypothesis H1b.

The difference of click intention between general and personalized ads is just as I hypothesized. The reason behind this difference could be that when a consumer sees a personalized ad, they might feel that their privacy is being violated. This feeling is higher for people with a high CPC, which leads to a lower click intention for consumers with high CPC. This effect is not noted when advertising with a general ad, because the ad does not use personal information and consumers do not feel privacy concerns when seeing these general ads. Since they do not feel privacy concerns there is no difference in behavior between consumers with low CPC and consumers with high CPC.

The effect of CPC on the willingness to share personal information was significant. The results showed that a higher level of CPC leads to a lower willingness to share personal information. According to the privacy calculus theory consumers make a risk-benefit analysis before sharing information. Based on my analyses, consumers with high CPC find the risks of sharing personal information higher than consumers with low CPC. It might even be that consumers with low CPC are so little concerned about who gets their information that they are willing to share everything with everyone. This can be seen in the results that consumers with a high CPC level are less inclined to share information compared to consumers with a low CPC level. This is consistent with H2. The results also showed that the effect on willingness to share personal information is negatively moderated by age, meaning that older people are less willing to share personal information. This is in line with the findings of Graeff and Harmon (2002) that older people don't want to share their credit card information. I also tested if there is a mediating effect on willingness to share personal information. Both value of privacy and value of ad relevance had a significant mediating effect on the willingness to share personal information. This again is in line with the privacy calculus theory and shows that consumers make an analysis between the costs (less privacy) and the benefits (relevant ads) of sharing personal information.

The effect of CPC on willingness to pay for privacy was not significant. This is not in line with previous research and with H3. It is possible that consumers are not willing to pay for privacy because they believe that companies should automatically respect their privacy. Another explanation is that since at the moment there is no market for privacy, consumers find the idea of paying for privacy strange and are therefore not yet willing to pay for privacy despite their privacy concerns.

The variable value of privacy did have a significant positive effect on willingness to pay for privacy. Consumers that value their privacy would very much like to keep this information private and are therefore willing to pay for their privacy. These results show that privacy conscientiousness is not enough to be willing to pay for privacy. The consumers have to value their privacy in order to be willing to pay for it.

The results showed that only age and education have an effect on the CPC level of consumers. Based on the research by Graeff and Harmon (2002), I expected that gender and income would also have a significant effect on CPC. They found that men have less privacy concerns then women and that consumer's with higher incomes have more privacy concerns.

The model that I used to find proxies that companies can use instead of CPC level showed that three out of the four proxies are significant. This means that companies can use the fact that a consumer allows cookies or not, the amount of times a consumer delete's cookies on his computer, and the fact that he reads the privacy policy or not, to predict a consumer's CPC level. They can use this proxy CPC level to predict click intention, willingness to share personal information and willingness to pay for privacy for their consumers.

6. IMPLICATIONS

The research from my thesis is useful for companies that are currently advertising on mobile applications or are planning to do so in the future. Companies are continually searching for ways to improve the effectiveness of their advertisement expenditures. These findings provide them with insight into how to better target consumers and personalize their advertisements in mobile applications.

The study shows that companies can optimize the click intention of personalized ads by targeting consumers with low CPC. This optimization would be even better if these low CPC consumers are somewhat older. However, companies should take into account the fact the older consumers are less willing to share information than younger consumers. This means that if companies want to personalize advertisements towards these consumers they can't use information shared by the consumers themselves. Instead companies should use other methods such as following a consumer's behavior on the internet to be able to offer them personalized advertisements. Companies can target these consumers using dynamic retargeting. This means that if a consumer views a certain product on a website, the advertisers should target this consumer with advertisement of that specific product.

Companies that are planning to have a campaign to collect consumer data, for example to increase their mailing list, should target younger consumers with low CPC. This way they have more chance of getting the results that they want out of the campaign.

For companies to be able to target consumers with the right level of CPC it is important for them to know consumers' CPC level. However, a consumer's CPC level is not a value that is known by either the consumer or by companies. Instead, companies can use 3 proxies to predict a consumer's CPC level. These proxies can be obtained by using software that can collect data about consumers' behavior. Companies can use the proxy CPC level of consumers to adapt their targeting so that is it most effective. If a consumer visits a website five times during a two month period, it means that the consumer does not delete cookies. It is likely that this consumer has a low CPC level. Companies can use this information to target this consumer with personalized ads. Another practical example is to keep track of consumers that do not read the privacy policies on websites and target them.

Companies should advertise inside mobile applications such as Scoupy. Scoupy has the possibility to target consumers based on their location. Consumers that are willing to share their location, personal information and preferences with an app are likely to have a lower CPC level. Companies can therefore reach these consumers and target them based on their preferences.

7. LIMITATION AND FUTURE RESEARCH

My research has a few limitations that present possibilities for future research. First, the study relies on intentions and not on actual behaviors. It would be interesting to explore how the finding of this study would change if it used data from a real mobile application combined with a follow-up questionnaire. Second, the click intention was measured using one general advertisement and one personalized advertisement. Future research should test the click intention on several products categories to see if it remains the same. Third, only four consumer characteristics were tested as CPC predictors. It is possible that there are other consumer characteristics that might be of influence. Future research could include more characteristics to study their effect on CPC. Fourth, I follow Baron and Kenny's (1986) method of mediation analysis and used the Sobel test to test the mediating effects in my research framework. Both the method and the test have been criticized by recent studies (Zhao et al 2010). According to Zhao et al (2010), mediation as well as nonmediation should be researched. Another criticism is that the Sobel test has low power. The limitations of this test could have influenced the results. For future research a bootstrap test of the indirect effect of *a x b* should be used to test the mediating effects. This method is more complex yet more reliable. Fifth, due to length constraints of the questionnaire, willingness to pay for privacy was measured using a very simple method. It would be interesting to thoroughly study the willingness to pay for privacy using another measure such as the BDM method. Finally, future researchers could hypothesize and test the mediating effects in this study to further analyze their effect.

8. CONCLUSION

This research introduces a new construct, Consumer Privacy Conscientiousness, to research how this consumer trait affects consumers' trade-off between privacy and ad-relevance regarding mobile advertising. This information is relevant to companies because a large group of consumers is using smartphones and companies are spending lots of money trying to reach these consumers. With the results of this study companies can target the right consumers. By doing so they can lower advertisement costs and get higher advertisement effectiveness.

Advertisements that use personal information should only be used when targeting consumers with a lower CPC level. This increases the chance of them clicking on the advertisement. Spending money on personalized advertisements to target high CPC consumers would be a waste of money because the feeling of intrusion of privacy will make these consumers not click on the advertisement.

The results also showed that companies can use proxies to predict the CPC level of consumers. This is useful because the CPC level is not a known factor. With these proxies companies can predict a consumer's CPC level and behavior and decide if it is worth it to target them.

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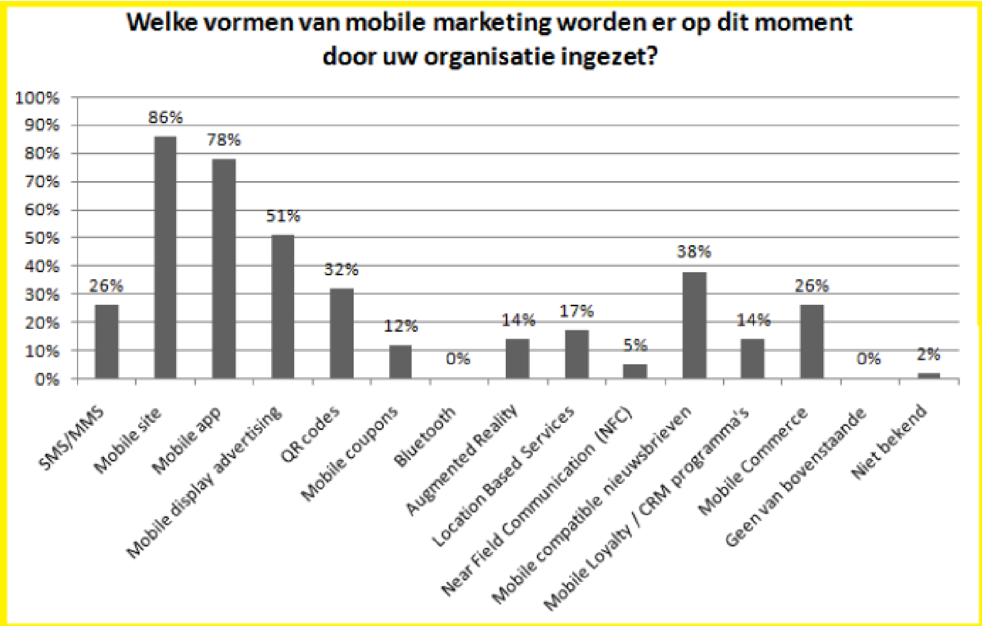
APPENDIX

APPENDIX A: Graph with the most used mobile marketing tools



Graph A1: Most used mobile marketing tools

APPENDIX B: Questionnaire research on privacy concern

Dear respondent,

I'm a Master student at the Erasmus University and I'm doing a research on privacy concerns on mobile phones. The results of this survey will be used in my thesis. This questionnaire will take about 5-7 minutes to fill in. There are no right or wrong answers. I would like your honest opinion, so please choose the answer that most represents the way you feel. Please answer all questions.

Thank you.
- Larisse Mercera

By filling in the questionnaire you have a chance of winning a photography course from De Rooij Fotografie. Between all completely filled questionnaires there will be a raffle off 5 smartphone photography online courses.

Read the statement below and choose which answer is most applicable.

I am aware of the risks related to privacy on the internet

- Strongly Agree
- Agree
- Somewhat agree/ Somewhat disagree
- Disagree
- Strongly disagree

--- *Read the statement below and choose which answer is most applicable.*

I think better privacy laws should be enforced on the internet

- Strongly Agree
- Agree
- Somewhat agree/ Somewhat disagree
- Disagree
- Strongly disagree

Read the statement below and choose which answer is most applicable.

Before sharing private information with a company I make sure it is safe

- Strongly Agree
- Agree
- Somewhat agree/ Somewhat disagree
- Disagree
- Strongly disagree

Read the statement below and choose which answer is most applicable.

I would like to control how companies use my private information

- Strongly Agree
- Agree
- Somewhat agree/ Somewhat disagree
- Disagree
- Strongly disagree

-- *Read the statement below and choose which answer is most applicable.*

I am concerned about possible threats to the personal information I have provided to companies

- Strongly Agree
- Agree
- Somewhat agree/ Somewhat disagree
- Disagree
- Strongly disagree

How concerned are you about the amount of personal information collected by companies?

- Very concerned
- Concerned
- Somewhat concerned
- Not very concerned
- Not concerned at all

How concerned are you that your personal information will be misused (sold to others) by companies?

- Very concerned
- Concerned
- Somewhat concerned

- Not very concerned
- Not concerned at all

How concerned are you that other people and companies can find your personal information on the internet?

- Very concerned
- Concerned
- Somewhat concerned
- Not very concerned
- Not concerned at all

How concerned are you about possible threats (hacks) to the personal information you have provided to companies?

- Very concerned
- Concerned
- Somewhat concerned
- Not very concerned
- Not concerned at all

Read the statements below and choose which answer is most applicable.

	Strongly Agree	Agree	Somewhat agree/ somewhat disagree	Disagree	Strongly disagree
I pay attention to detail					
I am always prepared					
I get chores done right away and do not put them off					
I like order					
I make a schedule before I do out my work					
I am exacting in my work					

Imagine that you have just opened an app on your mobile phone. You see the following advertisement.

How likely are you to click on this ad?

- Very likely
- Likely
- Somewhat likely
- Not very likely
- Not likely at all

Imagine that you are planning to buy a new Canon camera soon. You have looked up information about Canon camera's on your mobile phone. The next day while using one of you mobile applications you see the following advertisement.

How likely are you to click on this ad?

- Very likely
- Likely
- Somewhat likely
- Not very likely
- Not likely at all

The following question is about you willingness to share personal information inside a mobile app.

Please choose for each item how willing you are to share that information.

	Very willing	Willing	Somewhat willing	Not very willing	Not willing at all
Name					
Date of birth					
Location (via GPS)					
Telephone number					
Email address					
Payment information					

The following question is about privacy of your personal information in an app for you mobile phone.

How willing are you to pay for privacy?

- Very willing
- Willing
- Somewhat willing
- Not very willing
- Not willing at all

Read the statement below and choose which answer is most applicable.

It bothers me when companies ask for personal information

- Strongly Agree
- Agree
- Somewhat agree/ Somewhat disagree
- Disagree
- Strongly disagree

Read the statements below and choose which answer is most applicable.

Companies should not use someone's personal information unless it is authorized by the concerning individual

- Strongly Agree
- Agree
- Somewhat agree/ Somewhat disagree
- Disagree
- Strongly disagree

Read the statements below and choose which answer is most applicable.

Websites are allowed to track consumers in order to be able to send them personalized advertisements.

- Strongly Agree
- Agree
- Somewhat agree/ Somewhat disagree
- Disagree
- Strongly disagree

I would prefer to see advertisements that are relevant (to me) rather than random ads (that are not relevant to me).

- Strongly Agree
- Agree
- Somewhat agree/ Somewhat disagree
- Disagree
- Strongly disagree

To guarantee the quality of this survey, please choose the first answer (strongly agree).

- Strongly Agree
- Agree
- Somewhat agree/ Somewhat disagree
- Disagree
- Strongly disagree

In a few of the questions below they talk about cookies. Cookies are small files that are saved on your computer so that a website can recognize you on your next visit or can keep track of what you do on the website.

How frequently do you delete cookies?

- Never
- Once a month
- Once a week
- Every day
- After every browsing session
- I have never heard about cookies before

Do you make use of the private browsing option in your internet browser?

- Yes
- No
- I don’t know the private browsing option

Do you allow websites to place cookies on your computer?

- Yes, I allow (almost) all cookies
- No, I block (almost) all cookies
- I only allow cookies from websites that I visit regularly
- I don’t know

Do you read the privacy policies of the websites that you visit?

- Yes
- No
- Sometimes

To finish, I have some demographic questions. Please answer the questions below to help us segment the results of this survey. Thanks!

What is your age?

What is your gender?

- Female
- Male

What is your yearly income?

- < 20.000 euro
- Between 20.000 and 30.000 euro
- Between 30.000 and 40.000 euro
- Between 40.000 and 50.000 euro
- > 50.000 euro
- I don’t want to answer

What is your level of education?

- Did not complete high school
- High school graduate
- Some College (MBO)
- Bachelor's degree (HBO or WO bachelor)
- Master's degree
- Doctorate degree (PhD)
- I don't want to answer

If you would like to have a chance to win one of the 5 vouchers for the online course smartphone photography (worth 47 euro), then please fill in your email address. All surveys are anonymous and the answered will not be linked to your email address.

Thank you for filling in this survey.

APPENDIX C: Dutch version of questionnaire

Beste respondent,

Ik ben een Master student aan de Erasmus Universiteit en ik doe momenteel onderzoek naar de bezorgdheid over privacy op mobiele telefoons. De resultaten van deze enquête worden gebruikt in mijn scriptie. Het duurt 5 tot 7 minuten om deze vragenlijst in te vullen. Er zijn geen goede of foute antwoorden. Ik wil graag jouw eerlijke mening, dus kies steeds het antwoord die het meest overeenkomt met wat je voelt.
Vul alsjeblieft alle vragen in.
Dankjewel.
-Larisse Mercera

Maak kans op een cursus fotografie bij De Rooij Fotografie!
Onder alle volledig ingevulde vragenlijsten worden 5 cursussen smartphone fotografie verloot.

Lees onderstaande zinnen en kies het antwoord wat het meest van toepassing is.

Ik ben bewust van de risico's gerelateerd aan privacy op het internet

- Helemaal mee eens
- Mee eens
- Enigszins mee eens/ Enigzins niet mee eens
- Niet mee eens
- Helemaal niet mee eens

Ik vind dat er betere privacy wetten moeten komen voor op internet

- Helemaal mee eens
- Mee eens
- Enigszins mee eens/ Enigzins niet mee eens
- Niet mee eens
- Helemaal niet mee eens

Voordat ik mijn privé informatie deel met een bedrijf zoek ik uit of het veilig is

- Helemaal mee eens
- Mee eens
- Enigszins mee eens/ Enigzins niet mee eens
- Niet mee eens
- Helemaal niet mee eens

Ik wil graag de controle hebben over hoe bedrijven mijn privé gegevens gebruiken

- Helemaal mee eens
- Mee eens
- Enigszins mee eens/ Enigzins niet mee eens
- Niet mee eens
- Helemaal niet mee eens

Ik ben bezorgd over mogelijke risico's van de privé informatie die ik aan bedrijven heb gegeven

- Helemaal mee eens
- Mee eens
- Enigszins mee eens/ Enigzins niet mee eens
- Niet mee eens
- Helemaal niet mee eens

Hoe bezorgd ben jij over de hoeveelheid privé gegevens die bedrijven verzamelen?

- Heel bezorgd
- Bezorgd
- Een beetje bezorgd
- Niet zo bezorgd
- Helemaal niet bezorgd

Hoe bezorgd ben jij dat jouw privé gegevens worden misbruikt (verkocht) door bedrijven?

- Heel bezorgd
- Bezorgd
- Een beetje bezorgd
- Niet zo bezorgd
- Helemaal niet bezorgd

Hoe bezorgd ben jij dat andere mensen en bedrijven jouw privé informatie op internet kunnen vinden?

- Heel bezorgd
- Bezorgd
- Een beetje bezorgd
- Niet zo bezorgd
- Helemaal niet bezorgd

Hoe bezorgd ben jij over mogelijke risico's (hacks) van de privé informatie die jij aan bedrijven hebt gegeven?

- Heel bezorgd
- Bezorgd
- Een beetje bezorgd
- Niet zo bezorgd
- Helemaal niet bezorgd

Lees onderstaande zinnen en kies het antwoord wat het meest van toepassing is.

	Helemaal mee eens	Mee eens	Enigszins mee eens/ Enigzins niet mee eens	Niet mee eens	Helemaal niet mee eens
Ik besteed aandacht aan detail					
Ik ben altijd goed voorbereid					
Ik doe mijn taken direct en stel ze niet uit					
Ik hou van orde					
Ik maak een schema voordat ik mijn werkzaamheden uitvoer					
Ik ben veeleisend in mijn werk					

Beeld je in dat je net een app op je mobiele telefoon hebt geopend. Je ziet de volgende advertentie:

Hoe waarschijnlijk is het dat jij op deze advertentie klikt?

- Zeer waarschijnlijk
- Waarschijnlijk
- Enigszins waarschijnlijk
- Niet heel waarschijnlijk
- Helemaal niet waarschijnlijk

Beeld je in dat je binnenkort van plan bent om een nieuwe Canon camera te kopen. Je hebt informatie over Canon camera's opgezocht op je mobiele telefoon. De volgende dag krijg je in een app op je telefoon de volgende advertentie te zien:

Hoe waarschijnlijk is het dat jij op deze advertentie klikt?

- Zeer waarschijnlijk
- Waarschijnlijk
- Enigszins waarschijnlijk
- Niet heel waarschijnlijk
- Helemaal niet waarschijnlijk

De volgende vragen gaan over hoe bereid jij bent om jouw privé gegevens te delen in een app op je mobiele telefoon.

Kies voor elke item hoe bereid jij bent om deze informatie te delen.

	Zeer bereid	Bereid	Enigszins bereid	Niet heel bereid	Helemaal niet bereid
Naam					
Geboortedatum					
Locatie (via GPS)					
Telefoonnummer					
Emailadres					
Betaalinformatie (bankgegevens)					

De volgende vraag gaat over de privacy van je privé gegevens in een app voor je mobiele telefoon.

Hoe bereid ben jij om te betalen voor privacy?

- Zeer bereid
- Bereid

- Enigszins bereid
- Niet heel bereid
- Helemaal niet bereid

Lees onderstaande zinnen en kies het antwoord wat het meest van toepassing is.

Het zit me dwars als bedrijven vragen naar mijn privé gegevens.

- Helemaal mee eens
- Mee eens
- Enigszins mee eens/ Enigzins niet mee eens
- Niet mee eens
- Helemaal niet mee eens

Bedrijven mogen privé gegevens van iemand niet gebruiken tenzij het goedgekeurd is door de betreffende persoon.

- Helemaal mee eens
- Mee eens
- Enigszins mee eens/ Enigzins niet mee eens
- Niet mee eens
- Helemaal niet mee eens

Lees onderstaande zin en kies het antwoord wat het meest van toepassing is.

Websites mogen consumenten (en hun gedrag) op internet volgen om hen gepersonaliseerde advertenties te kunnen sturen.

- Helemaal mee eens
- Mee eens
- Enigszins mee eens/ Enigzins niet mee eens
- Niet mee eens
- Helemaal niet mee eens

Ik zie liever advertenties die relevant zijn (voor mij) dan algemene advertenties (die niet relevant zijn voor mij).

- Helemaal mee eens
- Mee eens
- Enigszins mee eens/ Enigzins niet mee eens
- Niet mee eens
- Helemaal niet mee eens

Om de kwaliteit van deze vragenlijst te waarborgen, kies het eerste antwoord hieronder (helemaal mee eens).

- Helemaal mee eens
- Mee eens
- Enigszins mee eens/ Enigzins niet mee eens
- Niet mee eens
- Helemaal niet mee eens

In enkele van de onderstaande vragen wordt gesproken over cookies. Cookies zijn kleine bestanden die worden opgeslagen op de computer zodat de website jou kan herkennen bij een volgend bezoek of kan bijhouden wat jij op de website doet.

Hoe vaak verwijder jij cookies op de computer?

- Nooit
- 1 keer per maand
- 1 keer per week
- Elke dag
- Na elke internet sessie
- Ik heb hiervoor nog nooit gehoord van cookies

Maak je weleens gebruik van de incognito venster optie (internetgeschiedenis en cookies worden dan niet opgeslagen) in je internet browser?

- Ja
- Nee
- Ik ken de incognito optie niet

Sta jij het toe dat websites cookies op je computer plaatsen?

- Ja, ik accepteer (bijna) alle cookies
- Nee, ik blokkeer (bijna) alle cookies
- Ik accepteer alleen cookies van websites die ik vaak bezoek
- Ik weet het niet

Lees jij het privacy beleid van de websites die je bezoekt?

- Ja
- Nee
- Soms

Tot slot nog enkele demografische vragen:

Vul alsjeblieft onderstaande vragen in zodat wij de resultaten van de enquête kunnen segmenteren. Bedankt!

Wat is jouw leeftijd?

Wat is jouw geslacht?

- Vrouw
- Man

Wat jouw jaarlijks inkomen?

- < 20.000 euro
- Tussen 20.000 en 30.000 euro
- Tussen 30.000 en 40.000 euro
- Tussen 40.000 en 50.000 euro
- > 50.000 euro
- Ik wil geen antwoord geven

Wat is het niveau van jouw hoogst voltooide opleiding?

- Ik heb de middelbare school niet afgemaakt
- Middelbare school afgemaakt
- MBO
- Bachelor diploma (hbo of wo bachelor)
- Master diploma
- Doctoraat
- Weet ik niet/ Ik wil geen antwoord geven

Als je kans wilt maken op 1 van de 5 vouchers voor de online cursus smartphone fotografie (t.w.v. 47 euro), vul dan jouw emailadres in.

Alle vragenlijsten zijn anoniem en de antwoorden zullen niet gekoppeld worden aan jouw emailadres.

Bedankt voor het invullen van deze enquête!

APPENDIX D: Constructs & Measures

Table D1: Construct and Measures [Source]

Consumer Privacy Conscientiousness (CPC) [Own development]
1. I am aware of the risks related to privacy on the internet
2. I think better privacy laws should be enforced on the internet
3. Before sharing private information with a company I make sure it is safe
4. I would like to control how companies use my private information
5. I am very concerned about possible threats to the personal information I have provided to companies

Response scale: 5= strongly agree, 4=agree, 3=somewhat agree/somewhat disagree, 2=disagree, 1=strongly disagree

Privacy Concerns [Similar to Smith et al 1996]
1. How concerned are you about the amount of personal information collected by companies?
2. How concerned are you that your personal information will be misused (sold to others) by companies?
3. How concerned are you that other people and companies can find your personal information on the internet?
4. How concerned are you about possible threats (hacks) to the personal information you have provided to companies?

Response scale: 5=very concerned, 4=concerned, 3=somewhat concerned, 2=not very concerned, 1=not concerned at all

Conscientiousness [International Personality Item Pool; Korzaan & Boswell 2008]
Which answer is most applicable?
1. I pay attention to detail
2. I am always prepared
3. I get chores done right away and do not put them off
4. I like order
5. I make a schedule before i do my work
6. I am exacting in my work

Response scale: 5=strongly agree, 4=agree, 3=somewhat agree/somewhat disagree, 2=disagree, 1=strongly disagree

Click Intention [Similar to Xu et al 2009]
1. How likely are you to click on this ad? (vignette low involvement product)
2. How likely are you to click on this ad? (vignette tailored product)

Response scale: 5=very likely, 4=likely, 3=somewhat likely, 2=not very likely, 1=not likely at all

Willingness to share personal information [Phelps et al 2000]
Please choose for each item how willing you are to share that information
1. Name
2. Date of birth
3. Location (via GPS)
4. Telephone number
5. Email address
6. Payment information

Response scale: 5=very willing, 4=willing, 3=somewhat willing, 2=not very willing, 1=not willing at all

Willingness to pay for privacy [Own development]
1. How willing are you to pay for privacy? (in an app for your mobile phone)

Response scale: 5=very willing, 4=willing, 3=somewhat willing, 2=not very willing, 1=not willing at all

Value of Privacy [Similar to Smith et al 1996]
1. It bothers me when companies ask for personal information
2. Companies should not use someone's personal information unless it is authorized by the concerning individual

Response scale: 5=strongly agree, 4=agree, 3=somewhat agree/somewhat disagree, 2=disagree, 1=strongly disagree

Value of Ad Relevance [Similar to Phelps et al 2000]
Which answer is most applicable?
1. Websites should be allowed to track consumers in order to be able to send them personalized advertisements.
2. I would prefer to see advertisements that are relevant (to me) rather than random ads (that are not relevant to me).

Response scale: 5=strongly agree, 4=agree, 3=somewhat agree/somewhat disagree, 2=disagree, 1=strongly disagree

Question for survey quality
1. Please choose the first answer (strongly agree)

Response scale: 0=strongly agree, 1=agree, somewhat agree/somewhat disagree, disagree, strongly disagree

Proxies to measure CPC without asking [Own development]
1. How frequently do you delete cookies?
Response scale: 2=never, 3=once a monthe, 4=once a week, 5=every day, 6=after every browsing session, 1=i've never heard about cookies before
2. Do you make use of the private browsing option in your internet browser?
Response scale: 3=yes, 2=no, 1=i don't know the private browsing option
3. Do you allow websites to place cookies on your computer?
Response scale: 2=yes, 4=no, 3=some, 1=i don't know
4. Do you read the privacy policies of the websites that you visit?

Response scale: 3=yes, 1=no, 2=sometimes

Demographics

1. Age

Response scale:

2. Gender

Response scale: 0=female, 1=male

3. Yearly income

Response scale: 1=up to 20.000 euro, 2=between 20.000 and 30.000 euro, 3=between 30.000 and 40.000 euro, 4=between 40.000 and 50.000 euro, 5=more than 50,000 euro, 9=i don't want to answer

4. Level of education

Response scale: 1=did not complete high school, 2=high school graduate, 3=some college, 4=bachelor, 5=master, 6=doctorate, 9=i don't want to answer

APPENDIX E: Descriptive Statistics

Descriptive Statistics

Variable	N	Minimum	Maximum	Mean	Std. Deviation
CPC1	291	2,00	5,00	4,2337	,74766
CPC2	291	2,00	5,00	4,2818	,75861
CPC3	291	2,00	5,00	3,7698	,92022
CPC4	291	2,00	5,00	4,4880	,72089
CPC5	291	1,00	5,00	3,8729	,92903
CPCaverage	291	2,40	5,00	4,1292	,55790
PC1	291	1,00	5,00	3,6529	,96837
PC2	291	1,00	5,00	3,8110	,96241
PC3	291	1,00	5,00	3,7251	,98961
PC4	291	1,00	5,00	3,8763	,93872
CONSC1	291	2,00	5,00	3,9347	,74685
CONSC2	291	2,00	5,00	3,7938	,76028
CONSC3	291	1,00	5,00	3,4880	,90727
CONSC4	291	1,00	5,00	4,0790	,79477
CONSC5	291	1,00	5,00	3,2784	,94038
CONSC6	291	1,00	5,00	4,0550	,74074
CLICKgen	291	1,00	5,00	1,3402	,66260
CLICKrel	291	1,00	5,00	2,6942	1,38437
WTS1	291	1,00	5,00	3,1856	1,17147
WTS2	291	1,00	5,00	2,7491	1,19581
WTS3	291	1,00	5,00	2,1065	1,04006
WTS4	291	1,00	5,00	1,8316	,97335
WTS5	291	1,00	5,00	2,5430	1,10206
WTS6	291	1,00	5,00	1,2405	,61912
WTSaverage	291	1,00	5,00	2,2761	,75148
WTP	291	1,00	5,00	2,6632	1,22474
ValPri1	291	1,00	5,00	3,9416	,90212
ValPri2	291	1,00	5,00	4,6735	,60454
ValPriaverage	291	2,00	5,00	4,3076	,60664
ValRel1	291	1,00	5,00	2,1924	1,05246
ValRel2	291	1,00	5,00	3,3024	1,10389
ValRelaverage	291	1,00	5,00	2,7474	,88119
Prox1	291	1,00	6,00	3,4021	1,18024
Prox2	291	1,00	3,00	1,9485	,87144
Prox3	291	1,00	4,00	2,9210	,68275
Prox4	291	1,00	3,00	1,6942	,62637
Proxaverage	291	1,25	3,75	2,4914	,53168
Age	291	16,00	80,00	48,9072	14,54582
Gender	291	1,00	2,00	1,4845	,50062
Income	144	1,00	5,00	2,4653	1,24549
Education	253	1,00	6,00	3,4862	1,00633

Table E1: Descriptive Statistics

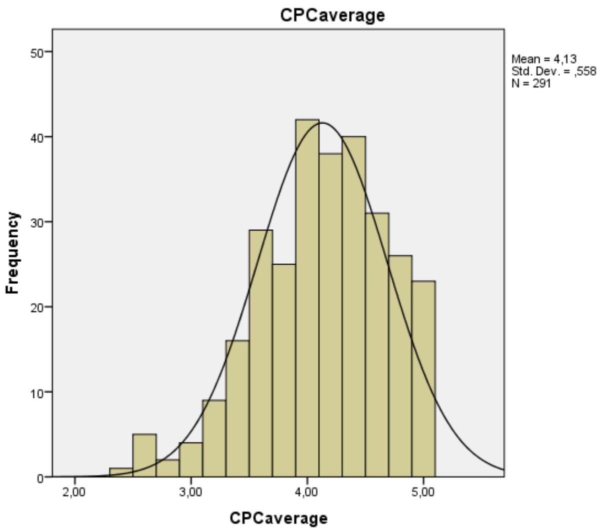
SPSS variable	Definition
CPC	Consumer Privacy Conscientiousness
CPCaverage	Computed average for CPC
PC	Privacy Concern
CONSC	Conscientiousness
CLICKgen	Click Intention for general ads
CLICKrel	Click intention for personalized ads
WTS	Willingness to share prívate information
WTSaverage	Computed average of WTS
WTP	Willingness to pay for privacy
ValPri	Value of privacy
ValPriaverage	Computed average of value of privacy
ValRel	Value of ad relevance
ValRelaverage	Computed average of value of ad relevance
Prox	Proxies
Proxaverage	Computed average of proxies

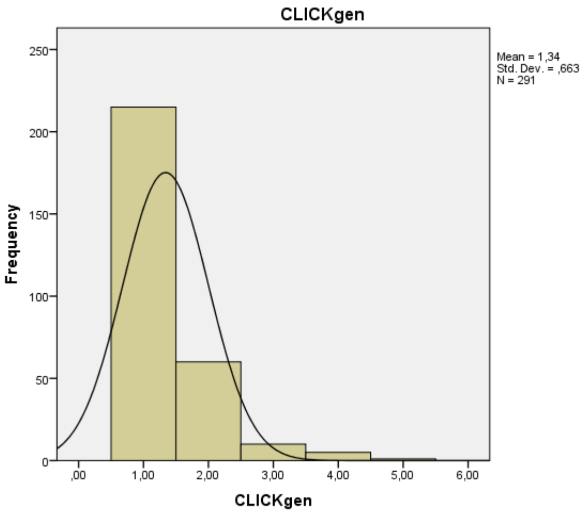
Table E2: Definition of the SPSS variables

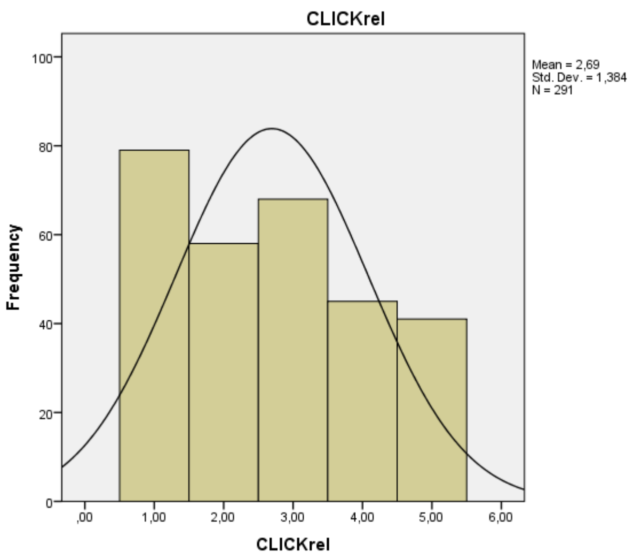
Scale	Cronbach's Alpha	Pearson's R
Consumer Privacy Conscientiousness	0.710	-
Willingness to share	0.821	-
Privacy Concern	0.882	-
Conscientiousness	0.780	-
Value of privacy	-	0.268
Value of ad relevance	-	0.336

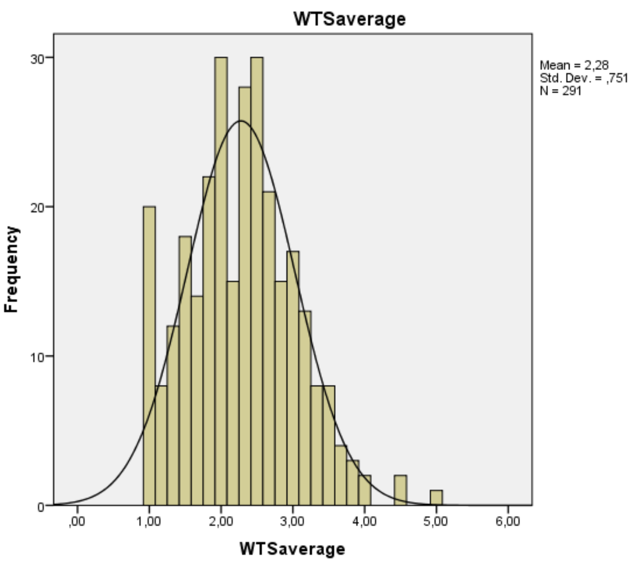
Table E3: Table with Cronbach's Alpha & Pearson's R

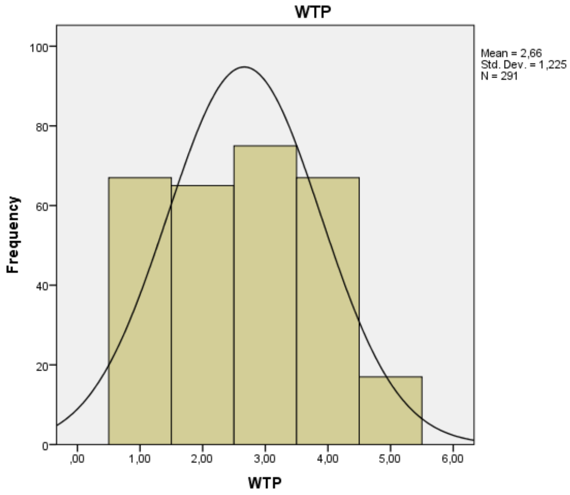
APPENDIX F: Graphical analyses

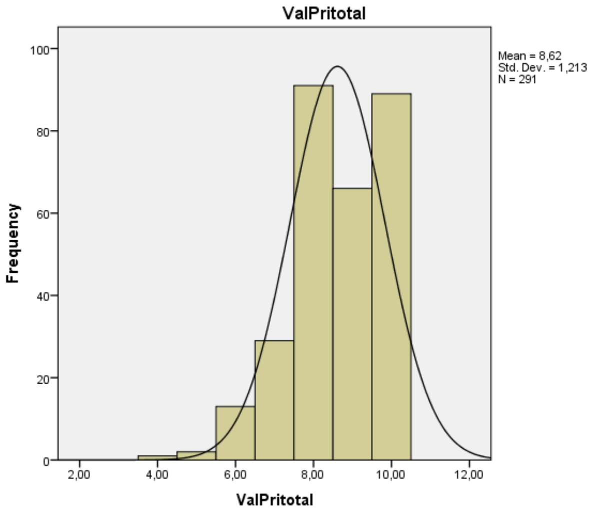


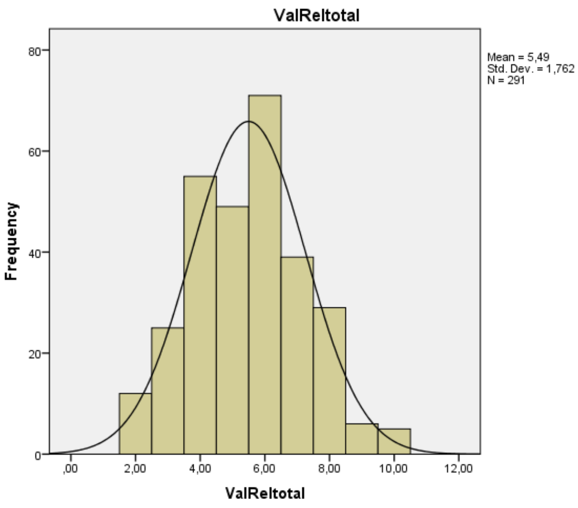







WTP
Mean = 2,66
Std. Dev. = 1,225
N = 291
Frequency
WTP


ValPritotal
Mean = 8,62
Std. Dev. = 1,213
N = 291
Frequency
ValPritotal


ValReltotal
Mean = 5,49
Std. Dev. = 1,762
N = 291
Frequency
ValReltotal

APPENDIX G: Table with correlations

Correlations

		CPCaverage	CLICKgen	CLICKrel	WTSaverage	WTP	ValPriaverage	ValRelaverage	Age	Gender	Income	Education	Proxaverage
CPCaverage	Pearson Correlation	1	,015	-,190**	-,336**	,096	,535**	-,169**	,376**	,173**	,147	-,239**	,435**
	Sig. (2-tailed)		,799	,001	,000	,101	,000	,004	,000	,003	,078	,000	,000
	N	291	291	291	291	291	291	291	291	291	144	253	291
CLICKgen	Pearson Correlation	,015	1	,366**	,205**	,103	-,107	,097	,059	,073	,116	-,118	,011
	Sig. (2-tailed)	,799		,000	,000	,078	,069	,097	,312	,214	,165	,060	,855
	N	291	291	291	291	291	291	291	291	291	144	253	291
CLICKrel	Pearson Correlation	-,190**	,366**	1	,229**	,088	-,079	,177**	,048	,040	,031	-,049	-,131*
	Sig. (2-tailed)	,001	,000		,000	,136	,182	,002	,411	,492	,715	,439	,025
	N	291	291	291	291	291	291	291	291	291	144	253	291
WTSaverage	Pearson Correlation	-,336**	,205**	,229**	1	,047	-,357**	,258**	-,239**	,050	-,057	-,004	-,159**
	Sig. (2-tailed)	,000	,000	,000		,424	,000	,000	,000	,399	,496	,947	,006
	N	291	291	291	291	291	291	291	291	291	144	253	291
WTP	Pearson Correlation	,096	,103	,088	,047	1	,138*	-,039	,057	-,082	,224**	-,125*	,066
	Sig. (2-tailed)	,101	,078	,136	,424		,019	,506	,334	,165	,007	,046	,264
	N	291	291	291	291	291	291	291	291	291	144	253	291
ValPriaverage	Pearson Correlation	,535**	-,107	-,079	-,357**	,138*	1	-,238**	,331**	,013	,047	-,213**	,234**
	Sig. (2-tailed)	,000	,069	,182	,000	,019		,000	,000	,827	,573	,001	,000
	N	291	291	291	291	291	291	291	291	291	144	253	291
ValRelaverage	Pearson Correlation	-,169**	,097	,177**	,258**	-,039	-,238**	1	-,191**	,005	-,051	,026	-,168**
	Sig. (2-tailed)	,004	,097	,002	,000	,506	,000		,001	,935	,546	,682	,004
	N	291	291	291	291	291	291	291	291	291	144	253	291
Age	Pearson Correlation	,376**	,059	,048	-,239**	,057	,331**	-,191**	1	,299**	,255**	-,158*	,218**
	Sig. (2-tailed)	,000	,312	,411	,000	,334	,000	,001		,000	,002	,012	,000
	N	291	291	291	291	291	291	291	291	291	144	253	291
Gender	Pearson Correlation	,173**	,073	,040	,050	-,082	,013	,005	,299**	1	,284**	,014	,246**
	Sig. (2-tailed)	,003	,214	,492	,399	,165	,827	,935	,000		,001	,831	,000
	N	291	291	291	291	291	291	291	291	291	144	253	291
Income	Pearson Correlation	,147	,116	,031	-,057	,224**	,047	-,051	,255**	,284**	1	,164	-,003
	Sig. (2-tailed)	,078	,165	,715	,496	,007	,573	,546	,002	,001		,051	,973
	N	144	144	144	144	144	144	144	144	144	144	143	144
Education	Pearson Correlation	-,239**	-,118	-,049	-,004	-,125*	-,213**	,026	-,158*	,014	,164	1	-,110
	Sig. (2-tailed)	,000	,060	,439	,947	,046	,001	,682	,012	,831	,051		,080
	N	253	253	253	253	253	253	253	253	253	143	253	253
Proxaverage	Pearson Correlation	,435**	,011	-,131*	-,159**	,066	,234**	-,168**	,218**	,246**	-,003	-,110	1
	Sig. (2-tailed)	,000	,855	,025	,006	,264	,000	,004	,000	,000	,973	,080	
	N	291	291	291	291	291	291	291	291	291	144	253	291

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

APPENDIX H: Regression models

Regression model: CPC-Click intention general ad

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,015[a]	,000	-,003	,66367	1,580

a. Predictors: (Constant), CPCaverage

b. Dependent Variable: CLICKgen

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,029	1	,029	,065	,799[b]
	Residual	127,291	289	,440		
	Total	127,320	290			

a. Dependent Variable: CLICKgen

b. Predictors: (Constant), CPCaverage

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1,267	,291		4,352	,000		
	CPCaverage	,018	,070	,015	,255	,799	1,000	1,000

a. Dependent Variable: CLICKgen

Regression model: CPC-Click intention personalized ad

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,190[a]	,036	,033	1,36157	1,660

a. Predictors: (Constant), CPCaverage

b. Dependent Variable: CLICKrel

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	20,012	1	20,012	10,794	,001[b]
	Residual	535,768	289	1,854		
	Total	555,780	290			

a. Dependent Variable: CLICKrel

b. Predictors: (Constant), CPCaverage

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	4,638	,597		7,768	,000		
	CPCaverage	-,471	,143	-,190	-3,285	,001	1,000	1,000

a. Dependent Variable: CLICKrel

Regression model: CPC-willingness to share personal information

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,336[a]	,113	,110	,70895	1,850

a. Predictors: (Constant), CPCaverage

b. Dependent Variable: WTSaverage

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	18,515	1	18,515	36,837	,000[b]
	Residual	145,253	289	,503		
	Total	163,768	290			

a. Dependent Variable: WTSaverage

b. Predictors: (Constant), CPCaverage

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	4,146	,311		13,335	,000		
	CPCaverage	-,453	,075	-,336	-6,069	,000	1,000	1,000

a. Dependent Variable: WTSaverage

Regression model: CPC-willingness to pay for privacy

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,096[a]	,009	,006	1,22117	1,869

a. Predictors: (Constant), CPCaverage

b. Dependent Variable: WTP

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4,026	1	4,026	2,700	,101[b]
	Residual	430,971	289	1,491		
	Total	434,997	290			

a. Dependent Variable: WTP

b. Predictors: (Constant), CPCaverage

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1,791	,536		3,345	,001		
	CPCaverage	,211	,129	,096	1,643	,101	1,000	1,000

a. Dependent Variable: WTP

Regression models: Mediator Value of Privacy

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,535[a]	,287	,284	,51330	2,022

a. Predictors: (Constant), CPCaverage

b. Dependent Variable: ValPriaverage

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	30,578	1	30,578	116,054	,000[b]
	Residual	76,146	289	,263		
	Total	106,723	290			

a. Dependent Variable: ValPriaverage

b. Predictors: (Constant), CPCaverage

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1,904	,225		8,459	,000		
	CPCaverage	,582	,054	,535	10,773	,000	1,000	1,000

a. Dependent Variable: ValPriaverage

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,396[a]	,157	,151	,69235	1,812

a. Predictors: (Constant), ValPriaverage, CPCaverage

b. Dependent Variable: WTSaverage

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	25,714	2	12,857	26,822	,000[b]
	Residual	138,054	288	,479		
	Total	163,768	290			

a. Dependent Variable: WTSaverage

b. Predictors: (Constant), ValPriaverage, CPCaverage

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	4,732	,339		13,952	,000		
	CPCaverage	-,274	,086	-,203	-3,175	,002	,713	1,402
	ValPriaverage	-,307	,079	-,248	-3,875	,000	,713	1,402

a. Dependent Variable: WTSaverage

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,192[a]	,037	,030	1,36340	1,665

a. Predictors: (Constant), ValPriaverage, CPCaverage

b. Dependent Variable: CLICKrel

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	20,425	2	10,212	5,494	,005[b]
	Residual	535,355	288	1,859		
	Total	555,780	290			

a. Dependent Variable: CLICKrel

b. Predictors: (Constant), ValPriaverage, CPCaverage

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	4,498	,668		6,735	,000		
	CPCaverage	-,514	,170	-,207	-3,024	,003	,713	1,402
	ValPriaverage	,074	,156	,032	,472	,638	,713	1,402

a. Dependent Variable: CLICKrel

Regression models: Mediator Value of Ad Relevance

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,169[a]	,029	,025	,87001	2,167

a. Predictors: (Constant), CPCaverage

b. Dependent Variable: ValRelaverage

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6,436	1	6,436	8,503	,004[b]
	Residual	218,749	289	,757		
	Total	225,186	290			

a. Dependent Variable: ValRelaverage

b. Predictors: (Constant), CPCaverage

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3,850	,382		10,091	,000		
	CPCaverage	-,267	,092	-,169	-2,916	,004	1,000	1,000

a. Dependent Variable: ValRelaverage

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,240[a]	,058	,051	1,34861	1,672

a. Predictors: (Constant), ValRelaverage, CPCaverage

b. Dependent Variable: CLICKrel

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	31,982	2	15,991	8,792	,000[b]
	Residual	523,798	288	1,819		
	Total	555,780	290			

a. Dependent Variable: CLICKrel

b. Predictors: (Constant), ValRelaverage, CPCaverage

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3,738	,688		5,435	,000		
	CPCaverage	-,408	,144	-,165	-2,836	,005	,971	1,029
	ValRelaverage	,234	,091	,149	2,565	,011	,971	1,029

a. Dependent Variable: CLICKrel

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,393[a]	,155	,149	,69330	1,795

a. Predictors: (Constant), ValRelaverage, CPCaverage

b. Dependent Variable: WTSaverage

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	25,334	2	12,667	26,353	,000[b]
	Residual	138,433	288	,481		
	Total	163,768	290			

a. Dependent Variable: WTSaverage

b. Predictors: (Constant), ValRelaverage, CPCaverage

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3,466	,354		9,804	,000		
	CPCaverage	-,406	,074	-,301	-5,480	,000	,971	1,029
	ValRelaverage	,177	,047	,207	3,767	,000	,971	1,029

a. Dependent Variable: WTSaverage

Regression model: Value of privacy-willingness to pay for privacy

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,138[a]	,019	,016	1,21519	1,865

a. Predictors: (Constant), ValPriaverage

b. Dependent Variable: WTP

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8,232	1	8,232	5,575	,019[b]
	Residual	426,764	289	1,477		
	Total	434,997	290			

a. Dependent Variable: WTP

b. Predictors: (Constant), ValPriaverage

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1,467	,512		2,867	,004		
	ValPriaverage	,278	,118	,138	2,361	,019	1,000	1,000

a. Dependent Variable: WTP

Regression model: Value of ad relevance-willingness to pay for privacy

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,039[a]	,002	-,002	1,22592	1,854

a. Predictors: (Constant), ValRelaverage

b. Dependent Variable: WTP

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,667	1	,667	,444	,506[b]
	Residual	434,330	289	1,503		
	Total	434,997	290			

a. Dependent Variable: WTP

b. Predictors: (Constant), ValRelaverage

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2,813	,236		11,935	,000		
	ValRelaverage	-,054	,082	-,039	-,666	,506	1,000	1,000

a. Dependent Variable: WTP

Regression model: Value of privacy –Click intention general ad

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,107[a]	,011	,008	,65995	1,563

a. Predictors: (Constant), ValPriaverage

b. Dependent Variable: CLICKgen

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1,452	1	1,452	3,334	,069[b]
	Residual	125,868	289	,436		
	Total	127,320	290			

a. Dependent Variable: CLICKgen

b. Predictors: (Constant), ValPriaverage

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1,843	,278		6,631	,000		
	ValPriaverage	-,117	,064	-,107	-1,826	,069	1,000	1,000

a. Dependent Variable: CLICKgen

Regression model: Value of ad relevance –Click intention general ad

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,097[a]	,010	,006	,66058	1,567

a. Predictors: (Constant), ValRelaverage

b. Dependent Variable: CLICKgen

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1,210	1	1,210	2,772	,097[b]
	Residual	126,110	289	,436		
	Total	127,320	290			

a. Dependent Variable: CLICKgen

b. Predictors: (Constant), ValRelaverage

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1,139	,127		8,968	,000		
	ValRelaverage	,073	,044	,097	1,665	,097	1,000	1,000

a. Dependent Variable: CLICKgen