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Will you tell me who you are?: The effect of consent strategies and incentives on privacy concerns

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Contents

Abstract

This paper uses data collected by an online survey to study the impact of companies consent strategies on customers' willingness to share their private data. The analysis also considers the moderating effect of 'incentive to join' offered to customers on data collection point. Hypotheses are formed regarding the Psychological Reactance Theory and Default Theory. The study has two main findings. First, customers develop psychological reactance in response to companies' consent strategies. The willingness to share private data increases in opt-in consent strategy, in which customers have more freedom. Secondly, monetary incentives have a positive impact on customers' willingness to share private data. Customers share their data when they are incentivized to do, in monetary settings. Together with the main findings, there are two second degree findings; the impact of age and social media usage. Age is positively correlated with privacy concerns. Older people are less likely to share their private data. Finally, customers spent more time on social media are more likely to share their private data when asked for it.

1. Introduction

1.1. Background over big data

According to *Science Daily*, 90 % of all the data in the world has been collected in the last two years (Sinteff, 2013). It is expected to double each year from now on. Many companies collect consumer data and exploit it for further analysis, to increase their profits or to sell such data or analyses of such data to third parties. By the help of the developing technology and decreasing data handling costs service providers, non-profit organizations, governments, firms collect data as a part of daily business activities. For instance, people generate 1.8

million likes and upload 200.000 photos on Facebook (Facebook , 2017). Around 100 hours of video are uploaded to YouTube every minute (Youtube, 2017). Google examines all contents sent or received via Gmail, analyzes keywords (Ramon Casadesus-Masanell, 2015). INRIX offers real time traffic condition reports by collecting data from users' mobile phones. Car rental company Avis Budget restructures marketing activities by using data collected from 40 million customers. By this, they improved marketing return on investment, customer experience, and long term customer value, says Black (Doolittle, 2016).

Academic research in marketing has also devoted strong attention to big data. Definition of Big Data in Tirunialli and Tellis (2014) study refers to the vast information, mostly belongs to individuals, collected and used for better understanding and prediction of behavior. It refers to datasets that traditional data processing techniques are insufficient to analyze due to its size and complexity (Wedel, 2016). Big data stands with great importance by making the information transparent, accurate, detailed and usable at the higher frequency. More specifically, big data can be defined by four characteristics named as 4 'V's; Volume (scale of data i.e. terra bytes), Velocity (streaming data, real time processing), Variety (forms of data i.e. text, pictures, audio), Veracity (reliability of data, is the data meaningful to solve the problem and free from biases, noise, abnormality) (Wedel, 2016). Big data will be the key to survive in the competitive environment. For example, retailers can increase operating margin, in the developed economies government administrators could save in operational efficiency improvements by simply using big data. In complex business environments, using sample selection methods do not provide the detailed information on differentiated clusters and lead incorrect analysis. Companies prefer to approach internal or external customers with tailored offers.

1.2. Targeted marketing

In this study, I focus on marketing related applications of big data analysis. Marketers believe that big data will revolutionize their targeted marketing actions. To begin with, they can use it to understand, predict and manage market conditions, customer demand by eliminating heterogeneity concerns (Desarbo W, 1997). Approaching from a marketing perspective, targeted marketing is the key benefit of analyzing big data. Marketing industry faced the reality that marketing mix decisions made by instincts or sample selection to understand the whole fall behind meeting competitive advantage of big data. John Wanamaker's famous saying 'half of my marketing budget is wasted and which half don't know' can be overcome by big data analysis. Iyer and colleagues (2005) refer marketing activities focuses on an individual level as targeted marketing. The potential of targeted marketing and pricing in household purchases has been proved previously (Robert E. McCulloch, 1996). For targeted, individual level marketing activities previous methods cannot compete with big data analysis. Tiruniliali and Tellis (2014) discussed the benefits of user generated content. Big data enables a continuous automated cycle to track changes in consumer preferences, due to its' characteristics mentioned earlier. Recently, companies prefer using targeted marketing for more effective and to the point advertisements. Despite the contrarian views (Bradlow, 2015), big data seems to be the most effective tool to overcome the biggest problem of targeted marketing; consumer addressability by identifying consumer preferences based on an individual level data. The term of consumer addressability means identifying customers by characteristics (Iyer, 2002). Overcoming customer addressability even provides the opportunity to approach consumers with targeted product modifications and pricing strategies (Iyer G. D., 2000).The combination of existing methodologies and new advancements such as big data statistics, machine learning can create a bright future for marketing science and big data (Chintagunta, 2016).

For instance, Google uses the Gmail data to capture pre-determined key words and phrases to examine users' tendencies and possible purchase behavior and sell this information to companies for targeted advertisements. Albert Heijn aggregates purchase history by incentive program and offers individual specific discounts or bonuses to consumers.

1.3. Privacy Concerns

On the other hand, all those big data includes distinctive personal data that can end up violating consumer's privacy. Consumer privacy is described as having control over the use of consumer information including or beyond search history, demographics and information facilitating profiling customer (Martin, 2017). Some of the data is collected by the consent of the consumer while the rest is not. Big data is gaining more and more importance every day and simultaneously increase concerns in consumers mind about privacy breaches. Law suits against well-known websites and increasing privacy protection acts stand as proof of this situation.

Surveys show that 89% of internet users prefer not to share their private data with companies if they think the company is not protecting their privacy (Mori, 2015). The study claims that people are more worried about data privacy than losing their income (Mori, Consumer Privacy Index, 2016). And also according to the research, the privacy concern is valid for all age groups (Gina Pingitore, 2013).

Reforms in data protection regulations are made by "2016, Regulation (EU) 2016/679 of The European Parliament and of The Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation)" and will be active by 25 May 2018. (The European Union Data Privacy Directive, 2000)

By the regulations to be effective as of 2018 in the European Union (The European Union Data Privacy Directive, p. 2012), the personal data can be processed only if the data subject has given consent. Consent can be derived via opt-in or opt-out strategies. The strategies are defined in Kumar's (2014) study. While some companies act more conservative regarding regulations others don't and set opt-in defaults or don't provide opt-out options. Considering the mentioned regulations and concerns, companies are becoming more forced to collect consumer data by their consent.

1.4. Existing Literature

Reviving the literature, we can see that researchers have been investigating several aspects of big data and privacy in the last couple of years. Conitzer and fellows (2012) studied the effects of anonymizing customers' profile on companies' profits. In their study, they examined whether it would be profitable for firms to use anonymized data as this method is also accepted by consumers. This allows companies to collect data while respecting consumers' privacy. They found out that anonymizing consumer data indeed lead to greater profit for companies.

Goldfarb and Tucker (2011) examined targeted online advertisings and consumers 'perception of obtrusiveness over targeted advertisings. They found that combination of targeting with obtrusiveness triggers consumers' negative perception and privacy concerns. Farley (2005) showed the improvement of interactive marketing, its effectiveness and the added value of interactive marketing when it is performed on an individual basis. Under the types of interactive marketing tools, they showed that companies invest 2% more on ‘opt-in’ strategy over opt-out strategy.

Hann and colleagues (2007) distinguished consumers between convenience seeker and information seller and studied their preference for monetary or non-monetary incentives in return of their private data. According to their research, convenience seekers prefer non-monetary incentives (time saving for frequent users) while information sellers prefer monetary incentives (worth $5, $10, $20) in return of their private data.

In another study, according to their frequency of past purchases, people are segmented as high value (frequent buyers) and low value (non-frequent buyers) to test personalized services (Varian, 2011). According to their study, companies can use big data and identify past purchases of each individual customer. By doing so, they can segment their customers as high value or low value and set their prices accordingly.

The opt-in and opt-out times, the impact of consumers´ characteristics over opt-in and opt-out times have been investigated by Kumar (2014). They identified the impact of marketing intensity on opt-in/opt-out times. They also pointed how to manipulate customers to extend opt-out times and increase their spending.

Acquisti and colleagues (2016) discussed that economics of privacy is not a one size fits all issue. They studied the value of private data and the value of privacy. Their study highlights that the optimal balance depends on the content and scenario. They also suggest that on most cases, power imbalance exists in private data collection. Customers suffer imperfect information on controlling their data. Also, the privacy concerns do not only address individual but also societal impacts. They underlined that customers are supposed to be informed by public authorities since the impact of customers' awareness is not an only individual level concern and has greater effects on society.

However, despite customers declare concern on sharing private data, Athey and colleagues (2017) mentioned the privacy paradox. Privacy paradox refers to the situation where one mentions it's privacy concern but disclose the private data when incentivized to do so. They conducted a field experiment with university students and found out small incentives (free pizza) creates a sharp contrast in respondents' behavior and their stated preference. They also showed that when protecting private data becomes costly, respondents give up their prior attitude and do not continue to protect their private data.

Privacy concerns are examined under a different perspective by Tsai and colleagues (2011). They approached the manner as leverage to manipulate customer behavior on companies' behalf. They unveil that some customers are likely to pay a premium to use privacy protected websites when privacy information is explicit and reachable. This finding also enables marketers to use privacy protection as a selling point.

1.5. Purpose of the study

Involving customers in the information privacy dialogue provides a transparent and open communication environment and increase company performance (Martin, 2017). However, a step prior to including customers in privacy dialogues, companies need to ask their permission before generating consumer data (Martin, 2017). In addition to the existing literature, the effect of companies' consent strategies scarce further investigation. The way firms approach consumers and ask them for their private data is what, in this thesis, I call a firm's *data consent strategy*. In other words, I define *data consent strategy* as the approach that a company uses to convince its consumers to disclose private, individual-level, data. In this study, I distinguish between three types of consent strategies: (1) opt-in strategy, (2) opt-out strategy and (3) forced consent strategy.

In an *opt-in strategy*, companies ask consumers their consent initially and then proceed subscription. In an *out-out strategy*, companies subscribe users as default and inform them about the option to unsubscribe (V.Kumar, 2014). In a *forced consent* strategy, companies force consumers to agree to disclose their data before they can use the company's products or services. The forced consent strategy is frequently used, among others, by online services). In such cases, unless consumers share their private data with the company, the company prevents them from accessing their website or app, or from using their online services. For instance, in the Gmail example, there is no option other than to renounce the use of service.

Despite the importance of big data and predictive analytics for marketing, and the potential impact of consumers' privacy concerns on the effectiveness of big data-based campaigns, there is a scarcity of empirical studies on the topic in the marketing literature. I aim to contribute literature by comparing the effectiveness of opt-in, opt-out and forced consent strategies on consumers' willingness to share their private data.

Independently of the data consent strategy used, firms can also motivate consumers to share their private data by giving them incentives for doing so. In this study, the incentives will be defined as *monetary incentives* and *non-monetary incentives*. The first type of incentive; *monetary incentives* include discounts, coupons, etc., i.e., financial benefits that result in a lower price for the service/good offered by the company to the individual consumer. As an example of monetary incentives, mobile device users are offered $15-$20 discounts on the Kindle tablets and e-readers purchases in exchange of targeted advertisements from Amazon. MasterCard offering ‘Priceless Surprises’ geographically targeting consumers by offering free flights to customers when they are at the airport.

The second type of incentives; *Non- monetary incentives*, are other benefits such time saving application, personalized facilitator for daily activities. As an example of non-monetary incentives, Amazon uses suggestion engine to recommend books at an individual level, specific to the user according to the browsing or purchase history on the website. Recommendation engine helps individuals save time on searching for books they would enjoy. The same methodology is also followed by Netflix. Another example is that Tesco built a kiosk at airports, that passengers can fill their information and shop while waiting for their flight. The products are delivered to their address by the time they arrive home. So they do not face an empty fridge.

Besides the consent strategy, I also examine the impact of monetary versus monetary incentives on consumers’ willingness to share data.

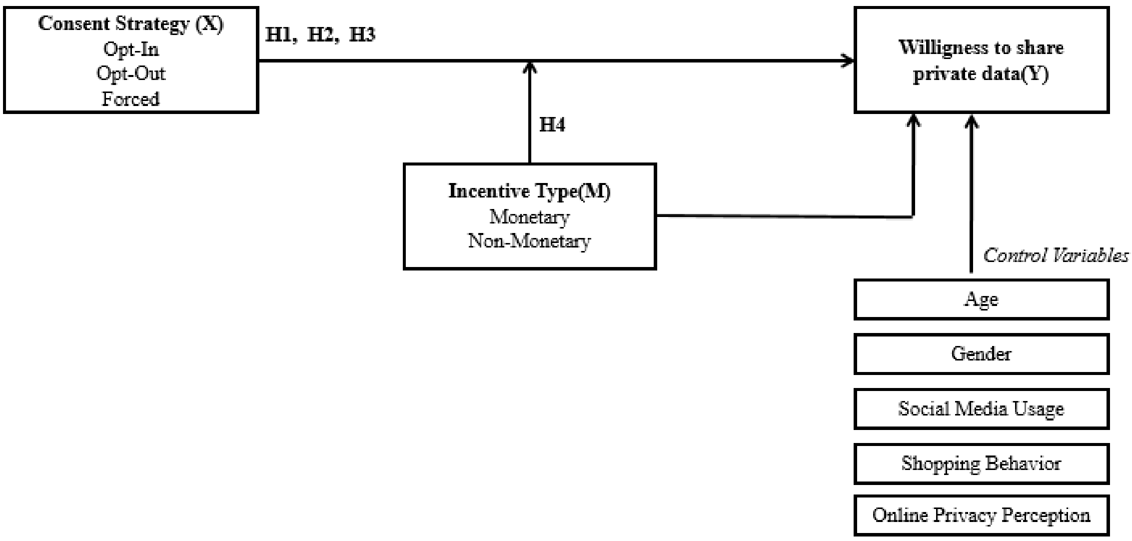
I theorize that incentives moderate the effect of consent strategy on consumers’ willingness to share private data. Specifically, a benefit offered by companies can convince customers to share personal data, as there is a sacrifice on customers’ side. Companies can encourage customers to disclose personal data by compensating their loss of privacy. Consumers weigh the convenience provided by the company on one hand and their private data on the other.

Marketers, market researchers, and managers would benefit knowing how to approach consumers in order to create a positive bond and collect consumer data for efficient marketing mix analysis. It is important to know what kind of trade-offs to offer. Companies also need to be aware of the psychological reactance of customers to the way of consent is asked. This study can guide decision makers on generating big data without creating a negative image in consumers mind that can damage companies´ brand equity.

2. Theory:

In this chapter, I discuss the theoretical background and the hypotheses. I summarize my conceptual framework in Figure 1."

Figure 1: Conceptual Framework



2.1. Data Consent Strategies and Psychological Reactance

Companies are trying to gather more data by accelerating the customers' consent stage. They shorten the process by default subscriptions, opt-out strategies or forced consent strategies. In opt-out strategy, companies do not have to wait for customers to decide and respond whether they agree to share data or not. In forced consent strategy, companies ask consent initially but by not providing alternative options, they expedite the decision making for customers. Consumers are losing the freedom to disclose private data under the chosen condition, to the desired parties and to the desired extend. In order to explain the effects of different data consent strategies on consumers' willingness to share private data, I draw upon the psychological reactance theory (Brehm, 1966). Figure 1, summarizes my theoretical framework.

According to Brehm (1966), when people are restricted in some way they feel a strong need to resist and fight back to gain their freedom. The theory states when people value their freedom more, the reactance is greater and more likely to result in a contrary response. When the freedom is threatened the reaction can be greater. Considering the psychological reactance theory also applies in consent strategy process, when consumers feel that they don't have control over their information disclosure or they are forced to share, this may reveal reactance against firms and harm companies' marketing activities. They may not only keep their data to themselves but also participate less in the commercial activities. Instead of revealing their private information, they can choose not to use the applications, not to subscribe memberships and as a result, limit their purchase.

Taking into account the consent strategies; in opt-in strategy personal data is collected if only customers agree to share where they poses the right to keep personal data and still use services. In opt-in consent strategy, companies first ask customers' consent before they start collecting data. Based on their permission, they collect and use the private data. Customers withhold the option to reject sharing private data and still maintain the relationship with the company. In opt-out strategy, personal data has already been collected prior to customers' approval. Companies collect and use private data for their benefit. Afterward, they inform the customer about data collection and what options do customers have. Customers are given the right to cease or continue to use services. In forced consent strategy, customers are not offered any option. They have to agree to share personal data.

Otherwise, they cannot use services offered by the company. The psychological reactance is positively correlated with the proportion of freedom that has been threatened (Brehm, 1966). If the consent strategies are ordered according to the proportion of freedom that has been threatened; I assume Opt-in consent strategy is expected to yield the least reactance among three options due to the fact that in this option where consumers are offered more freedom. After opt-in consent strategy, the opt-out setting is expected to create less reactance then forced consent strategy. Yet in opt-out settings, customers still withhold to cease data collection and maintain their relationship with the company. On the contrary, in forced consent settings, unless customers agree to share their private data they cannot maintain their relationship with the company. Therefore, I expect the reactance to be greater in opt-out strategy and forced strategy respectively.

In sum, I propose:

H1: Firm usage of an opt-in privacy policy increases consumers' willingness to disclose private data, as compared with firm usage of a forced consent privacy policy.

H2: Firm usage of an opt-out privacy policy increases consumers' willingness to disclose private data, as compared with firm usage of a forced consent privacy policy.

However, opt-in is also the strategy that is more likely to leave marketers with access to fewer data and therefore inefficient marketing decisions. According to the default theory, people tend to be influenced default options (Samuelson 1988; Johnson, 2011; Johnson 2003). In various sectors such as insurance, pensions, people are observed to take no action and continue with the default settings (Abadie 2006; Madrian 2001). It is shown that defaults save lives by the organ donations (Goldstein, 2003). Samuelson and colleagues show that people stick with the designated option as a getaway from a difficult decision making process (Samuelson, 1988).

In these past studies, three key reasons are mentioned to explain why the default effect exists. First, is the ease of not making decision and not putting any effort? Second, the belief that default option selected due to its merit of presenting a choice. Third, the default option may set a reference point and aggravate other options evaluation. Opt-in consent strategy protects consumers and provides them a broader space but what about companies? In the light of the mentioned studies, if the purpose is to gather relevant data in greater quantities, this type of strategy would not be the optimal option for companies. The majority of consumers would switch to not sharing data simply because of asking their consent in the first place rather than applying opt-out or forced consent strategies.

Therefore, in line with default theory (Samuelson 1988; Johnson 2011), I expect an opt-out privacy policy to leverage on our tendency to stick with defaults, making it easier and more likely that consumers are willing to share their data. In contrast, I expect an opt-in consent strategy leading consumers to be less willing to share their data. As a result, I propose:

H3: Firm usage of an opt-out consent strategy increases consumers' willingness to disclose private data, as compared with firm usage of an opt-in consent strategy.

While forced consent strategy can create negative impression and reactance in consumer response, opt-in strategy may provide ineffective results for marketers. For the optimal design, a balance needs to be found between not creating reactance and not decreasing data collection. Opt-out strategy, depending on the perception of consumers, can be the solution to this issue. If we position consent strategies on a linear line with the opt-in strategy on the left side and forced consent strategy on the right, the question is where consumers position opt-out strategy on this scale? Closer to opt-in, in middle or closer to forced consent? The benefit of using default settings for greater positive response and eliminating the reactance effect in consumers may be possible by opt-out strategy. The answer to this question is to be found in this study.

2.2. The Moderating Effect of Incentives

Besides the direct effect of data consent strategy on consumers' willingness to share data, through psychological reactance and defaults, incentives may also play an important role. The incentives are proven facilitators for marketers to collect consumer data (Stewart 2016; Hann 2007). Incentives are motivational devices to lead consumers into a desired behavior or choice. There are two major types of incentives: monetary and non-monetary. I aim to examine the moderating effect of monetary versus non-monetary incentives on the effect of a firm's data consent strategy on consumers' willingness to share data. Specifically, I argue that the effects of type of consent strategy used by firms (forced consent vs. opt-out vs. opt-in) on consumers' willingness to share data are possibly contingent on the presence and type of incentives used by firms to motivate consumers to share their data, for two main reasons.

First, monetary and non-monetary incentives make different aspects of a transaction salient to the consumer. Monetary incentives involve a monetary gain to the consumer, typically framed in terms of a lower price (e.g. discounts, coupons, cash rebates). In other words, monetary incentives focus the consumer's attention on the cost-side of the transaction, reducing it. In contrast, non-monetary incentives are framed in terms of the increased convenience or services provided by the firm (e.g., better recommendations, time saving, more customized interactions). In other words, non-monetary incentives focus the consumer's attention on the benefit-side of the transaction, increasing it.

Second, monetary and non-monetary incentives may have different effects on different types of consumer. Hann and colleagues (2007) distinguish between convenience seekers (who are motivated by benefits providing convenience rather than financial gains and information sellers (who are motivated by financial gains rather than benefits providing convenience). They then show that non-monetary incentives accomplish desired motivational effects for convenience seekers (but not for information sellers). This condition is more applicable when customers visit the web page more frequently (more than once a week). As the visit frequency increase, customers are more likely to value convenience; time saving.

Taken together, these arguments suggest that the type of incentive (non-monetary vs. monetary) may moderate the effect of data consent strategy on consumers' willingness to share data. In fact, incentives may have both a direct effect on consumers' willingness to share data or an interaction effect with the data consent strategy and increase the performance of certain strategies.

As mentioned earlier, non-monetary incentives provide convenience for customers. Since opt-out strategy provides the greatest ease to agree on private data disclosure, because of default settings, this consent strategy has a common denominator with non-monetary incentives; convenience for customers. Therefore, an interaction effect can be observed.

H4: *Non-monetary incentives (time saving, facilitating) in comparison to monetary incentives may increase the effectiveness of opt-out consent strategies on consumers' willingness to share private data*.

There are other variables that can influence consumers' willingness to share data and, therefore, need to be controlled for in my model. For instance, the type of shopping behavior exhibit by consumers may dictate different levels of willingness to share private data. Marketing researchers typically consider two types of shopping behavior: utilitarian and hedonic (Barry J. Babin, 1994). Hedonic shoppers can be more likely to ignore the privacy concerns. This type of consumers can be affected by monetary incentives rather than non-monetary incentives to maintain the joy of shopping. The shopping behavior of consumers will be kept as the control variable. In addition, different socio-demographic variables, such as age and gender may influence consumers' willingness to share private data. Finally, certain behavioral variables, especially those capturing the relationship a consumer has with digital media and data (e.g. social media usage, digital literacy), may also influence her or his willingness to share data. I will control for these in my model.

3. Methodology

The hypotheses are tested by the ordinary least squares regression analysis, using the cross section data collected through a survey. The study aims to understand the companies' consent strategy' impact on customers' willingness to share private data. The moderating effect of incentive type offered to customers also included in the study. A 3 (consent strategy; opt-in, opt-out and forced) x3 (incentive type; monetary, non-monetary and no incentive) within subject design is employed.

The survey was sent to 221 respondents via an anonymous link and 146 of them filled the questions completely. Only the 146 complete answers are used in the analysis. In methodology section, I will describe the research design and the model used.

3.1 Research Design

3.1.1 Independent Variables

In order to test my theory-based hypotheses, I designed and run a survey experiment. I used a within-subjects design. The online questionnaire mainly consists two set of alternatives (stimuli) with three levels of dimensions (attributes) each. Subjects are asked to give their likelihood to share their private data. In the context of online privacy, dimensions are the Web site's Consent Strategy (Companies' approach to reaching user's personal data & subscription on their website) and the Incentive to Join (website's incentive offer for each user who agree to share their personal data.) 9 alternatives are identified with full combinations of 3x3 levels. Taken together, trade-offs among 6 dimensions are needed to be assessed— three benefit outcomes and three privacy outcomes. I created three outcomes for web site's consent strategy about user's personal data (opt-in, opt-out and forced consent strategies) and three outcomes for incentive rewards(10% discount for 1 year, personalized recommendations of clothes for the user and no incentive). Monetary incentive is selected as 10% discount instead of the amount in currency. 10% is picked from Stremersch and Tellis' (2002) paper. The respondents are from various nations with different economic conditions. In order to eliminate the subjective value of monetary incentive, discount percentage is used. In addition, an enduring discount could also cause unbalanced value for customers. The time frame is limited by one year.

Beside the 9 alternatives (stimuli), subjects are also asked for gender, age, shopping behavior and online privacy perception as control variables. Shopping behavior scale is adopted from Dhar and Wertenbroch's (2000) study and aims to segment the subjects as utilitarian or hedonic on Yes/ No questions. In addition to the scale, a shopping behavior question for self-assessment on a 10 point scale is added to the control variable questions. The second scale, online privacy perception of subjects is measured with Yes/No questions (Tom Buchanan, 2006). This scale segments subjects based on their value to online privacy.

In order to measure the consent strategy and incentive to join, questions are created from scratch.

3.1.2 Dependent Variable

In the survey, we asked subjects to rank 9 alternatives (see Table 3.1.2.1) for an online fashion store that represented different combinations of web site's data gathering policy & Incentive rewards. The subject is asked to rank the stimuli on a 10 point scale, according to his or her preferences (0; Not at all likely to share my private data, 10; Very likely to share my private data). A brief explanation is given to the respondents on top of the page lists profiles and likelihood scales. The explanation aims to guide respondents on how to evaluate the questions and in which condition they are facing the questions. In the explanation before the questions, private data is also explained to respondents. Search history and purchasing behavior is given as examples for private data.

Table 3.1.2.1 Profiles

Consent Strategy	Incentive Type	Situation
Opt in	Non-monetary	1
Forced Consent	Monetary	2
Opt- out	Non- monetary	3
Opt- out	No Incentive	4
Opt- in	No Incentive	5
Opt- out	Monetary	6
Opt- in	Monetary	7
Forced Consent	Non- monetary	8
Forced Consent	No Incentive	9

The process proceeded as follows: a link of survey shared with subjects: the experimental task and the meanings of the dimensions were explained to subjects in beginning of survey, later the subjects ranked the 9 stimuli based on their personal preferences on how likely they would agree to share their personal data in each of these different conditions.

3.2 Model

Linear regression models the relationship between variables. In this method, variables are defined as either dependent (endogenous) or independent (exogenous) variables. The causal analysis will be performed to test hypothesizes.

There are several analyses to measure the relationship between independent and dependent variables. Analysis techniques are differentiating based on the number and type of variables; nominal, ordinal, interval, ratio. In the analysis, the multiple linear regression models will be used as there are several exogenous variables (Consent Strategy of individual 'i', Incentive to Join for individual 'i', Interaction effect of Consent Strategy and Incentive to Join of individual 'i') and one dependent variable (Willingness to share private data of individual 'i'; WTSPD_i). Model also includes control variables (Age of individual 'i', Gender of individual 'i', Social Media Usage of individual 'i', Shopping Behavior of individual 'i' and Online Privacy Perception of individual 'i'*)*

The hypothesizes and control variables suggest the following equation;

Equation 1:

$$WTSPD\_i = \beta 0 + \beta 1*ConsentStrategy\_i + \beta\ 2*IncentiveToJoin\_i +$$
$$\beta 3*(ConsentStrategy\_i*IncentiveToJoin)\ \_i + \beta_4*ShoppingBehavior\_i + \beta_5*Age\_i +$$
$$\beta_5*Gender\_i + \beta_6*SocialMediaUsage\_i + \beta_7*OnlinePrivacyPerception\_i + e\_i$$

3.3 Data Analysis

After collecting data, next stage involves calculation of coefficients for each exogenous variable. SPSS 24 was used to analyze the correlation between variables.

Regression analysis treats exogenous variables as numerical; therefore I first coded exogenous variables as numerical values. The coefficients are measured by consent strategy and incentive type manipulations;

Opt Out= opt-in consent strategy; 0/ opt-out consent strategy; 1

Opt In= opt-in consent strategy; 1/ opt-out consent strategy; 0

Non-Monetary= Monetary incentive; 0/ non-monetary incentive; 1

Monetary= Monetary incentive; 1/ non-monetary incentive; 0

Due to the dummy variable trap (the scenario where exogenous variables are multi-collinear), one level of each alternative (The forced consent strategy and no incentive alternative) was discarded from the analysis. While interpreting the results, the forced consent strategy and no incentive alternatives are be taken as the base value and results are analyzed in comparison to base values.

The OLS regression analysis treats respondents as different observations and may cause bias. In OLS regression, every respondent is treated like different observations for each of the nine profiles. Therefore, a general linear regression analysis with repeated variable was run to control for repeated observations. The significance values of exogenous variables in both analysis results are the same. Therefore, the analyses are carried as OLS regression.

The results show that model has a low level of R^2 (Table 3.3.2). In order to decide which model to apply, first mixed model analysis used. In the analysis, the information criterions show which model has a better fit for the analysis. The lower value of information criterion points the model to be used. According to the Information Criteria's model including the control variables provides a better understanding for the analysis (Table 3.3.1). The model without the control variables has .37 R^2 which is slightly higher than the model with the control variables. Comparing the models, R^2 has no major difference and information criteria suggests the model with control variables. Therefore, the analysis carried with the model including control variables of gender, age, shopping behavior and online privacy perception.

Table 3.3.1 Information Criteria to select ideal model

Model	-2 Restricted Log Likelihood	AIC	BIC
With control variables	5823.171	5827.171	5837.305
Without control variables	6500.605	6502.608	6507.781

Table 3.3.2 Model Summary

Model	R Square	Adjusted R Square
1	.33	.19

4. Results

This section covers the survey experiment responses and the results of hypothesizes. Results are interpreted according to the *p=.05* significance value. While reading the results, please consider the caveat of omitted variables since the model has a low level of R^2 and 2adjusted R^2. The issue with the R^2 will be further discussed in the 'Limitations and Discussions' chapter.

In the Table 4.1 below, the coefficient values for each exogenous variable are listed;

According to the main effect results, the Age, Social Media Usage, Consent Strategy and Incentive Type have a significant impact on willingness to share private data.

Opt-in Consent strategy has a .580 unit positive impact on willingness to share private data, in comparison to forced consent strategy (*p=.004*). Proceeding from the results, the H_1 *'Firm* *usage of an opt-in privacy policy increases customers' willingness to disclose private data, as compared with firm usage of a forced consent privacy policy'* is supported by this study.

However, unlike Opt-in consent strategy, Opt-Out Consent strategy is not significantly different than forced consent strategy. (*p=.501*). As a result, the H_2 *'Firm usage of an opt-out privacy policy increases customers' willingness to disclose private data, as compared with firm usage of a forced consent privacy policy.' and* H_3 *'Firm usage of an opt-out consent strategy increases customers' willingness to disclose private data, as compared with firm usage of an opt-in consent strategy'* are not supported by the findings.

Incentive type also drives customers to share private data. Monetary incentives are significantly different than no incentive condition with .478 increase (*p=.016*). According to the analysis, non-monetary incentives have no significant impact on customers' willingness to share private data in comparison to no incentive condition (*p=.247*).

Age and willingness to share private data have a negative correlation. An increase in age results in .251 unit decrease in willingness to share data (*p=.018*). This can be interpreted as the older age increases customers privacy concerns.

On the other hand, the amount of social media usage has a positive impact on willingness to share private data. When customers spend more time on social media, they are .283 unit more likely to share private data (*p=.009*).

Table 4.1: Main effects of consent strategies, incentive types and control variables on willingness to share private data

Variables	Unstandardized B	Standardized B	Sig.
Opt-in	.580	.097	.004
Opt-out	.134	.022	.501
Monetary	.478	.080	.016
Non-monetary	.230	.039	.247
Age	-.251	-.070	.018
SocMedUse	.283	.076	.009
Gender	-.154	-.026	.392
DescribeYou	.000	.000	.993
Apt	.121	.019	.512
RegPP	-.289	-.051	.114
ReadPP	-.003	-.001	.990
LookPC	-.229	-.040	.232
ReadLA	.126	.021	.570
Constant	**3.746**		**.000**

As the second step, the regression is run with the interaction effects. Based on the information criteria in the mixed model analysis, including the interaction effects doesn't improve the model's reliability (Table 4.2).

Table 4.2: Information Criteria

Model	-2 Restricted Log Likelihood	AIC	BIC
Without interaction	5823.171	5827.171	5837.305
With interaction	5824.191	5826.191	5837.266

Based on the results, the interaction effect of consent strategy and incentive type doesn't provide additional value. All interaction effects are insignificant. (Interaction of Opt in consent strategy and monetary incentives *p=.779*; Interaction of Opt in consent strategy and non-monetary incentives *p=.297*; Interaction of Opt out consent strategy and monetary incentives *p=.262*; Interaction of Opt out consent strategy and non-monetary incentives *p=.334*).

Considering the insignificant interaction of consent strategy and incentive type, H_4 *'Non-monetary incentives (time saving, facilitating) in comparison to monetary incentives may increase the effectiveness of opt-out consent strategies on consumers' willingness to share private data.'* Is not supported by the findings.

In conclusion hypothesis,

Accepted; **H1**: Firm usage of an opt-in privacy policy increases customers' willingness to disclose private data, as compared with firm usage of a forced consent privacy policy.

Rejected; **H2**: Firm usage of an opt-out privacy policy increases customers' willingness to disclose private data, as compared with firm usage of a forced consent privacy policy.

Rejected; **H3**: Firm usage of an opt-out consent strategy increases customers' willingness to disclose private data, as compared with firm usage of an opt-in consent strategy.

Rejected; **H4:** Non-monetary incentives (time saving, facilitating) in comparison to monetary incentives may increase the effectiveness of opt-out consent strategies on consumers' willingness to share private data.

Table 4.3; Interaction effects of consent strategies and incentive types on willingness to share private data

Variables	Unstandardized B	Standardized B	Sig.
Opt-in	.796	.133	.021
Opt-out	-.205	-.034	.552
Monetary	.341	.057	.322
Non-monetary	.242	.041	.481
OptinMon	-.137	-.015	.779
OptinNonMon	-.508	-.057	.297
OptoutMon	.545	.061	.262
OptoutNonMon	.470	.052	.334

Age	-.251	-.070	.018
SocMedUse	.282	.076	.009
Gender	-.153	-.026	.393
DescribeYou	.000	.000	.992
Apt	.121	.019	.513
RegPP	-.289	-.051	.114
ReadPP	-.003	-.001	.990
LookPC	-.229	-.040	.232
ReadLA	.126	.021	.572
Constant	3.791		.000

5. Discussion

5.1 Limitations

The model is selected based on the information criteria results of the mixed model analysis. The selected model has a .33 R^2 value. However, the R^2 of the other models are slightly higher than the selected model by .04. In this chapter, I will discuss the reasons behind the low level of R^2. This condition indicates that model lacks omitted variables. The analysis is composed of consent strategies and incentives as exogenous variables. Based on the R^2, there are more important factors that lead customers to share their private data.

Based on previous research, trust is a salient component of diminishing customers' privacy concerns (Aiken, 2006). The effect of trust for companies is ignored in this study. According to Aiken and Boush's (2006) study, trust promotes customers' willingness to engage with companies. Trust may play a bigger role in customers' mind than companies' consent strategy or incentive type to offer.

The negative perception of control over personal data could be another variable that effects customers' willingness to share data. Lwin and colleagues (2007), studied that customers answer negatively to companies' privacy activities when a power imbalance is in place. Another method to eliminate the contrary response, caused by reactance, can be creating a positive perception over balance in control of the personal data. Offering customers control through all process, can promote their willingness to share private data. The effect of control is also not included in the scope of this analysis.

Findings are also subject to other limitations such as;

Data is not collected from subjects who are studied prior to conducting the survey. In this sense, subjects 'awareness level of privacy policies is not measured. As Tsai and colleagues (2011) offered, when customers are aware of the privacy protection level of companies, they are willing to pay a premium to use secured services. However, in this paper, the awareness level of customers is ignored. This situation may cause omitted variable impact.

Also performing within subject design might be insufficient to manipulate different profiles. Applied design might lead respondents to rank and compare the consent strategies, incentives. As a result, respondents might develop a bias in their answers.

The survey is conducted based on the imaginary conditions of online purchases. However, private data is also collected under different conditions such as; filling forms while applying to get a loan from banks, registering for courses/ training. Response to consent strategies and incentives might be different under these conditions.

5.2 Managerial Implications

How marketers and managers interpret the results and apply to marketing decisions? This question is aimed to be answered in this chapter.

Marketers should be aware of that default theory is not valid in private information sharing. Based on the survey analysis, easiness of opt-out default settings do not provide further value for companies and still result in a contrary response. The analysis proves that customers develop reactance in the collection of private data. In contrast to the expected situation in hypothesis 2 and 3, opt-out consent strategy also develops reactance like forced consent strategy. Customers are more likely to share private data when companies ask prior to collect their data. Even though companies prefer opt-out or forced consent strategies, opt-in consent strategy provides further value in the end. Customers prefer not to use the services under forced consent strategy and prefer to unsubscribe under opt-out consent strategy. However, using opt- in consent strategy eliminates the contrary effects of reactance and promotes private information sharing. Marketers should consider that reactance developed by customers can damage customer- company engagement. If we recall the Psychological Reactance Theory, customers can develop contrary response and negative feelings due to the reactance.

Also, there are other salient dimensions for customers. Incentives are one example for it. In the study, it was proved that monetary incentives (i.e. discounts, coupons, and bonus) promote customers to share their private data. Conversely, non-monetary incentives (i.e. time savings, personalized recommendations) are not considered as an encouragement to share private data. With regard to inflate the number of customers sharing private data, marketers can benefit from the monetary incentives. Indeed offering incentives increase the costs for companies. Yet, benefits of fact based marketing decisions can contribute overall success of the marketing activities.

Control variables of this study can guide companies on their market segmentation for private data collection activities. Social media usage and age appear to be important factors that influence the concern level of customers to share private data.

People, who use social media more often, are easier to approach for marketers. Marketers can focus more on customers who use social media less relatively. High level of social media usage already provides an advantage and enables marketers to invest more resources on other customers.

Age is also another factor that has an impact on willingness to share data. The older age decreases the likelihood that customers sharing their private data. Marketers should consider the age as an important factor on segmenting customers.

Taken together, companies can manipulate customer behavior by approaching with opt-in consent strategy and monetary incentives.

6. Conclusion

In this paper, the consent strategies and incentives, that might mitigate customer’s concerns over sharing their private data, are analyzed. To that end, the psychological reactance theory and default theories are applied to define research questions and hypothesis. The theories are tested by General Linear Regression Model considering the repeated measures. 10 point Likert scale is used to test the hypothesis, collected from 146 survey respondents. Respondents are not selected based on defined criteria. Hypothesis, which may stipulate that customers have privacy concerns, empirically validated based on mentioned theories. Similarly, the hypothesis confirmed that the psychological reactance theory is valid for sharing private data whereas the default theory is not.

This research can contribute companies by pointing how to define consent strategies and incentives to convince customers to share their private data. Results distinctly show that consent strategy is valued by customers. Therefore, companies can exploit this by designating their consent strategy more effectively. Often mentioned the benefit of choosing the effective consent strategy is eliminating contrary response from customers on collecting their private data and using the related data in marketing mix decisions. Asking customers their consent prior to collecting their private data is considered as a positive approach and achieves the expected outcome; increased willingness to share private data.

Perhaps the least surprising output is that offering incentives for customers also promotes sharing private data. Results show that monetary incentives are valued by customers as a motivation.

Due to the limited time and resources, this study doesn't cover many aspects that might be major contributors to promote private data sharing. There are questions needs further research;

- What is the customers' awareness level of privacy policies and how does it affect companies' data collection procedure?
- Does having control over the private data shared with companies mitigate privacy concerns and therefore increase willingness to share private data?
- To what extent, Customers' trust for the brand, facilitates companies' consent strategies?
- Do the technological capabilities of companies effect customer perception of privacy protection?

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