# The effect of privacy belief and privacy concern on consumers' willingness to share personal information for personalized online product recommendations


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**Abstract**

This study builds on previous research by developing a model based on the theory of planned behavior and the utility maximization theory to explain the effectiveness of online personalization recommendations including the perceived value of a personalized recommendation and the consumer's privacy concern and privacy belief. The results of the research show that consumers' willingness to share personal information and thereby the effectiveness of online personalized recommendations depends on the expected added value of a personalized recommendation, the level of privacy belief and the level of general privacy concern. Furthermore, the results suggest that the negative effect of general privacy concern on the willingness to share can be offset by a high level of privacy belief. This emphasizes the importance for managers to try to increase the level of privacy belief where possible. However, caution should be taken when creating trust-building cues to increase privacy belief. Furthermore, contrary to the expectations, the non-personalized recommendation was valued significantly higher than the personalized recommendation. Lastly, the results of this study support previous research that suggest personalized recommendations for experience products are perceived more useful than for search products.

*Keywords*: Online product recommendation; Personalization; Privacy concern; Privacy belief; Trust-building strategies

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# 1 Introduction

Online personalization has received a great amount of attention among academic researchers. By gathering data about customer's online behavior, retailers can develop personalized service offers which can increase the service relevance and consequently the customer adaption (Aguirre, Mahr, Grewal, de Ruyter & Wetzels, 2015). These online personalization offers can often generate additional sales (Postma & Brokke, 2002) and increase the level of consumer's loyalty toward the retailer (Srinivasan, Anderson, Ponnavolu, 2002). Furthermore, personalization is also an important vehicle in improving customer satisfaction and retention (Chellapa & Sin, 2005). Although there are multiple ways of offering personalized services, one of the most promising strategies is making personalized recommendations (Senecal & Nantel, 2004, p. 159). Online personalized recommendations can help customers find the products they would like to purchase by producing a list of recommended products for each individual customer (Cho, Kim & Kim., 2002). Recently, more and more companies are adopting this strategy. Examples of such online retailers that are offering online personalized recommendations include Netlix, Bol.com, Amazon and Albert Heijn.

However, previous research has shown that personalization does not always lead to positive effects. While personalization can improve the usefulness and the intention to use the recommendation service, it can also decrease the intention if the users perceive that too much of their information has been collected and used (Lee & Lee, 2009). This is in line with the results of Aguirre et al. (2005) which showed that the rejection of personalized advertisements often stem from feelings of vulnerability which arise when the consumers lack a sense of control over the situation and experience a state of powerlessness. However, this research of Aguirre et al. concerns the adoption of personalized online advertisements which is different than personalized services (such as product recommendations) due to the difference in perceived benefits (Awad & Krishnan, 2006). Fitzsimon and Lehmann (2004) have found that in certain circumstances recommendations can play an undesirable role from the perspectives of both the recommending agent and the person receiving the recommendation. Unsolicited recommendations can lead to consumers not only ignoring the agent's' recommendations but intentionally contradicting them. This is in line with the psychological reactance theory which states that people react against attempts to control their behavior and against threats to their freedom of choice (Lee & Lee, 2009).

The personalization paradox and the findings from previous research lead to an important question for managers about when and how personalized recommendation services should be implemented. In order to be able to provide consumer-driven personalized services, it is important for firms to target consumers who are willing to provide the necessary information (Awad & Krishnan, 2006). Therefore, the effectiveness of online personalized recommendations partially depends on the willingness of the targeted consumers to provide their personal information. In order for consumers to decide whether or not to share personal information, a trade-off needs to be made between their perceived value of the personalized service and the potential suffering due to negative consequences of sharing their personal information (Awad & Krishnan, 2006). Chellappa and Sin (2005) have developed a model to predict consumers' usage of online personalization services as a result of the trade-off between their perceived value of the personalization and their concern for privacy.

This study will build on the previous research by developing a model based on the theory of planned behavior and the utility maximization theory to explain the effectiveness of online personalization recommendations including the perceived value of a personalized recommendation and the consumer's privacy concern and privacy belief. According to the theory of planned behavior, the evaluation and the chance of a certain outcome combined will influence the behavioral choice (Azjen, 1991). When there is both a high perceived chance as well as substantial consequences then and only then will there be a significant influence on the decision. In the context of personalized online recommendations, both the privacy belief (the subjective probability that consumers belief that their information will be treated fairly) as well as the general privacy concern (the evaluation of how big the damage would be if their information is not treated fairly) would need to be sufficient in order for it to have an effect on the willingness to share privacy sensitive information.

By comparing the expected value for non-personalized and personalized recommendations and the willingness to share personal information for a personalized recommendation across different situations, the effectiveness of personalized recommendations is aimed to be explained. Furthermore, this study also examines potential trust-building strategies which can be implemented in online personalized recommendation settings. Altogether, this leads to the following research question: *How can the effectiveness of personalized online recommendations be explained and improved?*

This paper continues with an overview of the literature, which explores the research topics. Based on previous literature, a conceptual framework is developed and several hypotheses are drawn. Next, the research method is described. This is followed by a presentation and analysis of the results of the study. At last, the discussion and conclusion of the research are covered.

## 2 Literature review

### *2.1 Online product recommendations*

When customers are faced with multiple alternatives, more effort is needed to make decisions. Too many options can result in a decrease in motivation to choose or a decrease in the satisfaction with the finally chosen option (Schwartz, 2004). Recommendations often play a role in the decision making process by reducing the difficulty associated with choosing between the alternatives and increasing the confidence associated with it (Fitzsimons & Lehmann, 2004). Especially online, where the amount of choices can be overwhelming, recommendations can be very helpful. This section will cover the different types of online product recommendations and subsequently explore the value of personalized online recommendations.

Recommendations can be distinguished based on the type of information sources which can be impersonal versus personal and the type of provided information which can be personalized or non-personalized. Online recommendations from personal independent sources can for example be made on social media, online discussion forums or as testimonies on retail websites (Senecal & Nantel, 2004). This type of online consumer sharing is often referred to as electronic WOM (Cheung, Luo, Sia, & Chen, 2009). Other recommendations providing non-personalized information include the best-selling items for a certain product class or the items recommended according to the opinion of an expert in a specific product category (Kwon, Cho & Park, 2009). Furthermore, electronic decision-making aids such as recommender systems can be classified as impersonal information sources that provide personalized information to consumers (Senecal & Nantel, 2004). This last source of recommendations will be the topic of interest in this paper. These online personalized recommendations can help customers find the products they would like to purchase by producing a list of recommended products for each individual customer (Cho, Kim & Kim, 2002). Research has shown that recommendations from information sources offering personalized recommendations have a greater propensity to be followed compared to non-personalized recommendations (Senecal & Nantel, 2004).

Personalized recommender systems can suggest new products to consumers based on their previous purchase behavior (Lawrence, Almasi, Kotlyar, Viveros & Duri, 2001) or based on collaborative filtering which is based on a user's similarity to other users and their preferences (Montgomery & Smith, 2009). Collaborative filtering is a typical user-based method (Kwon et al., 2009) and makes use of the known preferences of a group of users in order to make recommendations or predictions of the unknown preferences for other or new users (Su & Khoshgoftaar, 2009). Furthermore, recommendation systems can make use of attributes, such as items viewed, demographic data, subject interests and favorite artists (Linden, Smith & York, 2003). An example of an online retailer that uses these attributes in their recommendation algorithms to personalize the online webshop for each customer is Amazon.com. Furthermore, recommendations can also be based on information from social networks. Research has shown that users in online social networks share similar interests with the social partners and that online social networks can have significant value as a useful information source for recommendations (Lee, 2013).

As mentioned before, the demand for recommendations originates from the complexity of the decision process. Therefore, the perceived value of product recommendations can be depending on the type and complexity of the decision process. For example one determinant that could influence the effect of recommendations on consumers' product choices is the type of product that is recommended (Senecal & Nantel, 2004). Senecal & Nantel (2004) have found that recommendations for experience products have a higher propensity to be followed than recommendations for search products. Search products are dominated by product attributes, for which consumers can acquire full information by inspection of the product prior to the purchase while experience products on the other hand cannot be evaluated prior to purchase and use of the product (Nelson, 1970). Examples of search products are calculators, mobile phones and athletic shoes (Senecal & Nantel, 2004; Bei, Chen & Widdows, 2004). Wine, dinners at new restaurants and travel packages are examples of experience products (Senecal & Nantel, 2004; Bei et al., 2004).

Besides the fact that recommendations are perceived less useful for certain types of products, also in certain circumstances recommendations can play an undesirable role. Fitzsimon and Lehman (2004) have found that unsolicited recommendations that contradict initial impressions can lead to consumers not only ignoring the agent's recommendation but intentionally contradicting them. This is in line with the psychological reactance theory which states that people react against attempts to control their behavior and against threats to their freedom of choice (Lee & Lee, 2009). Lee and Lee (2009) found that recommendation systems allow individual consumers to determine the best alternatives with the least amount of effort and in this way overcoming the information overload problem, but on the other hand some users may feel that their freedom to choose is restricted and threatened. Furthermore, product recommendations may not always make the decision process easier. Recommendation lists containing highly accurate product recommendations are often less diverse (Gan & Jiang, 2013). Especially when the product recommendation list contains too many products or when the recommendation seem to be too similar, product recommendations may make it more difficult for the consumer to choose.

In conclusion, recommendation lists containing not too many or too similar product recommendations can help consumers in the decision process by reducing the difficulty associated with choosing between the alternatives and increasing the confidence associated with it (Fitzsimons & Lehmann, 2004). Online personalized recommendations, in particular, can help customers find the products they want to purchase by producing a list of recommended products for each individual customer (Cho et al., 2002). Even though advice or information in general is perceived desirable in the decision making process, recommendations can be perceived less useful in cases where the consumers do not need (such as for search products) or want (unsolicited recommendations) advice.

### *2.2 Personalization paradox*

Personalization aims to maximize business opportunities by delivering the right content to the right person at the right time. By gathering data about customer's online behavior, retailers can develop personalized service offers which can decrease the customer's effort in the decision making process and can increase the service relevance and consequently the customer adaption (Aguirre et al., 2015). These online personalization offers can often generate additional sales (Postma & Brokke, 2002) and can increase the level of consumer's loyalty toward the retailer (Srinivasan, Anderson, Ponnavolu, 2002).

However, research has shown that personalization does not always lead to desirable outcomes. This is referred to as the personalization paradox and concerns the fact that depending on the context, personalization can be both an effective as well as an ineffective marketing strategy (Aguirre et al., 2015). While personalization can improve the usefulness and the intention to use the recommendation service, it can also decrease the intention if the users perceive that too much of their information has been collected and used (Lee & Lee, 2009). This is in line with the results of Aguirre et al. (2015) which showed that a greater personalization can either lead to an increase in service relevance resulting in an increase in customer adoption or in a decrease in customer adoption. In this latter case, the rejection of personalized advertisements often stems from feelings of vulnerability which arise when the consumers lack a sense of control over the situation and experience a state of powerlessness. This vulnerability can be explained by the reactance theory and arises when consumers front a personalized cue (Aguirre et al., 2015). However, according to Aguirre et al. (2015) trust-building strategies such as transferring trust from a media context or signaling trust with certain cues can offset this experience of vulnerability.

### *2.3 Willingness to share personal information*

In order to be able to provide consumer-driven personalized services, it is important for firms to target consumers who are willing to provide the necessary information (Awad & Krishnan, 2006). Therefore, the effectiveness of online personalized recommendations can depend on the willingness of the targeted consumers to provide their personal information. According to Awad and Krishnan (2006) a consumer's willingness to share this information online depends on the evaluation of the outcome of the online profiling. Consumers need to make trade-offs when deciding whether or not to share personal information for shopping benefits (Phelps, Nowak, & Ferrell, 2000). In order to understand this decision from an economic perspective, the utility maximization theory can be used. This framework has been criticized, since consumers do not tend to make a financial cost-benefit analysis of social contracts with unpredictable outcomes (Hoffman, Novak & Peralta, 1999, p. 132-133). However, previous research does suggest that while consumers might not compute an exact cost-benefit analysis for the sharing of personal information, they do weight the involved trade-off. This is known as the privacy calculus, which is concerned with a consumer's assessment of the usage of the personal information against the potential suffering due to negative consequences of sharing personal information (Awad & Krishnan, 2006, p. 18). Furthermore, research has shown that the willingness to provide personal information also depends on the specific types of personal information requested (Phelps et al., 2000). Consumers seem to be most willing to provide demographic and lifestyle information and least willing to provide personal identifiers or financial information.

In conclusion, in order to assess the willingness to share personal information besides the type of personal information requested, both the consumers' perceived value of the personalized service and their privacy-related concerns are important. In the following section the consumers' concerns for privacy will be explored.

### *2.4 Privacy concern and privacy belief*

The increased focus on the consumer and the emergence in personalization strategies has increased the demand for personal information. This has had a significant impact on consumers sense of anxiety regarding their personal privacy. Previous research has suggested that consumers' concerns about privacy can have significant negative consequences on firm trust and ultimately on purchasing intentions (Eastlick, Lotz, & Warrington, 2006; Li, Sarathy & Zang, 2008). Privacy concern and privacy belief are both terms that reflect this consumers' anxiety regarding their personal privacy. These two terms will be defined in the following section. Furthermore, the following section will explore both the causes and the effects of privacy concern and privacy belief.

Chellapa and Sin (2005) define privacy concern as the degree to whether the consumers believe their information is collected and treated fairly by a specific firm. However, this often referred to as privacy belief, which is situation dependent. It is about the subjective probability that consumers believe their private information is protected as expected by a specific online vendor (Li et al., 2008, p. 41). Privacy concern, on the other hand concerns the individual's personality trait or general tendency to worry about information privacy (Li et al., 2008, p. 41). In order to avoid confusion, the term general privacy concern will be used for the general tendency to worry about privacy and the term privacy belief will be used for the subjective probability that consumers believe their private information is protected as expected by a specific online company (which in some articles is called privacy concern).

Research has shown that general privacy concern has a negative effect on privacy related behavioral intentions (Li et al., 2008). Individuals who have a high privacy concern have lower privacy protection beliefs when interacting with vendors in general and consequently may be less willing to provide personal information to complete online transactions. According to Bandyopadhyay (2009), the lack of willingness to share personal information online, as well as the rejection of e-commerce and even unwillingness to use the internet are all possible consequences of online privacy concerns. Research has suggested that older, female and less educated people are more concerned about threats to their personal privacy (Milne & Rohm, 2000). Other factors that may influence online general privacy concerns are the consumer's cultural surroundings or background. Bandyopadhyah (2009) suggests that the power distance, individualism, masculinity and uncertainty avoidance indexes of the consumers' culture will be related to their general privacy concerns.

Li et al. (2008) have also found a significant effect of privacy belief on privacy-related behavioral intentions. Therefore, it is in a company's best interests to try to increase privacy belief as much as possible. According to Sheehan and Hoy (2000) there are multiple attributes that influence consumers privacy belief. Consumer awareness, information usage, information sensitivity, familiarity with the firm, compensation, and trust-building strategies are all factors which can have an effect on consumers' privacy belief (Sheehan & Hoy, 2000;

Chellapa & Sin, 2005). First of all, consumers' privacy belief can be triggered when consumers become aware of the fact that firms have collected and used their personal information. Examples of situations in which consumers can become aware of these practices are when they face a highly personalized cue or when they receive unsolicited promotions related to recent transactions. This will consequently lead to a lower degree of privacy belief which is the subjective probability that consumers believe their private information is protected as expected by a specific online vendor (Li et al., 2008, p. 41). Furthermore, consumers become more concerned if marketers use information beyond the original transaction or when they simply don't know how their information is being used (Sheehan & Hoy, 2000). Also, the degree to which a consumer is concerned depends on the type of information that is collected and used. The more sensitive the information, the more concerned the consumer will be. For example, consumers appear to be less concerned about the collection and usage of information related to product purchases and media habits compared to the collection and usage of financial data, medical records and social security numbers (Sheehan & Hoy, 2000). Furthermore, the familiarity with the entity can have a positive impact on consumers' privacy belief (Sheehan & Hoy, 2000; Li et al., 2008; Chellapa & Sin, 2005). An important aspect of the familiarity is the degree of trust a consumer has with a firm. Research has shown that consumers who trust the firm are concerned less about their privacy and are more willing to share personal information (Sheehan & Hoy, 2000).

In conclusion, general privacy concern is about the consumers' general tendency to worry about privacy while privacy belief is more situation dependent and is about the degree to whether consumers believe their information is collected and treated fairly by a specific firm. Both can have a an impact on consumers' behavioral intentions. It is in a firm's best interests to try to increase privacy belief the utmost by for example implementing trust-building strategies.

### *2.5 Trust-building strategies*

Trust is a psychological state comprised of the intention to accept vulnerability based on positive expectations of a firm's intentions or behaviors (Rousseau, Sitkin, Burt, & Camerer, 1998). This section will first explain the importance of trust-building strategies and will continue with exploring some trust-building strategies that can be implemented in the context of online recommendation services.

Due to information asymmetries and customer uncertainty, trust is especially important in online settings (Aguirre et al., 2015). As mentioned in the section about the personalization paradox, research has shown that a higher personalization can lead to a rejection of personalized advertisements due to feelings of vulnerability and that trust-building strategies can offset this experience of vulnerability (Aguirre et al., 2015). This is in line with the findings of Chellapa & Sin (2015), which suggest a positive effect of trust-building factors on the likelihood of using personalized services. Therefore, trust-building strategies can have a direct effect on the willingness to provide personal information for a recommendation. Furthermore, Chellapa & Sin (2005) have suggested that trust-building strategies can be used to increase privacy belief and therefore might have an indirect effect on consumer's willingness to share personal information as well.

Aguirre et al. (2015) have suggested two types of strategies that advertisers could pursue to build more trust in their advertisements. Online advertisers could capitalize the potential spillover of trustworthy websites to their advertisement or they can use signaling cues. In the context of online recommendation services, especially trust signaling cues can be beneficial. Examples of signaling trustworthiness are privacy or security disclosures, seals of approval and awards from neutral sources (Wang, Beatty & Foxx, 2004).

### *2.6 Theory of planned behavior*

According to the theory of planned behavior, an individual's behavior can be determined by the intention to perform the behavior, which in turn is predicted by three factors: attitude toward the behavior, subjective norms and the perceived behavioral control (Ajzen, 1991). The more favorable the attitude and subjective norm are concerning a certain behavior and the greater the perceived behavioral control; the stronger should the intention be to perform the behavior.

The importance of the three predictors may be dependent on different situations and behaviors (Ajzen, 1991, p. 189). Therefore, in some situations only one or two of the three factors might have a significant impact on the intention to perform the behavior. The theory of planned behavior has been successfully applied in predicting multiple different types of behaviors. Scholars have found that the theory of planned behavior can successfully predict an individual's intention to use an information system (Mathieson, 1991), weight loss behavior (Schifter & Azjen, 1985), intention to visit a green hotel (Han, Hsu, & Sheu, 2010), hunting behavior (Hrubes, Azjen & Daigle, 2001) and health-related behaviors (Godin & Kok, 1996).

The main takeaway of the theory is that each factor is a function of the importance of an attribute and the evaluation of an attribute. The first factor, attitude toward the behavior, for example, depends on the interaction between the behavioral beliefs and the outcome evaluations (Ajzen, 1991, p. 188). Behavioral belief is the subjective probability or chance that the behavior will lead to a particular outcome and the outcome evaluation is the rating of the desirability of the outcome. Therefore, the evaluation and the chance of a certain outcome combined will influence the attitude toward the behavior and consequently the intention and behavioral choice. When there is both a high perceived chance as well as substantial consequences then and only then will there be a significant influence on the decision. In the context of personalized online recommendations, both the privacy belief (the subjective probability that consumers belief that their information will be treated fairly) as well as the general privacy concern (the evaluation of how big the damage would be if their information is not treated fairly) need to be sufficient in order for it to have an effect on the willingness to share privacy sensitive information.

### *2.7 Literature gap*

Previous research has shown that personalization, depending on the context, can both be an effective as well as an ineffective marketing strategy (Aguirre et al., 2015). A greater personalization can lead to a higher degree of service relevance or usefulness resulting in a higher customer adoption of personalized online advertisements. On the other hand, due to an increase in feelings of vulnerability a greater personalization can also result in a lower customer adaption. However, due to the difference in perceived benefits, differences can be expected between the adoption of personalized advertisements and personalized services such as recommendation (Awad & Krishnan, 2006).

In order to be able to provide consumer-driven personalized services, it is important for firms to target consumers who are willing to provide the necessary information (Awad & Krishnan, 2006). Therefore, the effectiveness of online personalized recommendations can depend on the willingness of the targeted consumers to provide their personal information. In order for consumers to decide whether or not to share personal information, a trade-off needs to be made between their perceived value of the personalized service and the potential suffering due to negative consequences of sharing their personal information (Awad & Krishnan, 2006). This study will build on the previous research by developing a model based on the theory of planned behavior and the utility maximization theory to explain the effectiveness of online personalization recommendations including the perceived value of a personalized recommendation and the consumer’s privacy concern and privacy belief.

## 3 Conceptual framework

Based on previous research, several hypotheses are drawn and these are visualized in a conceptual framework (see figure 1).

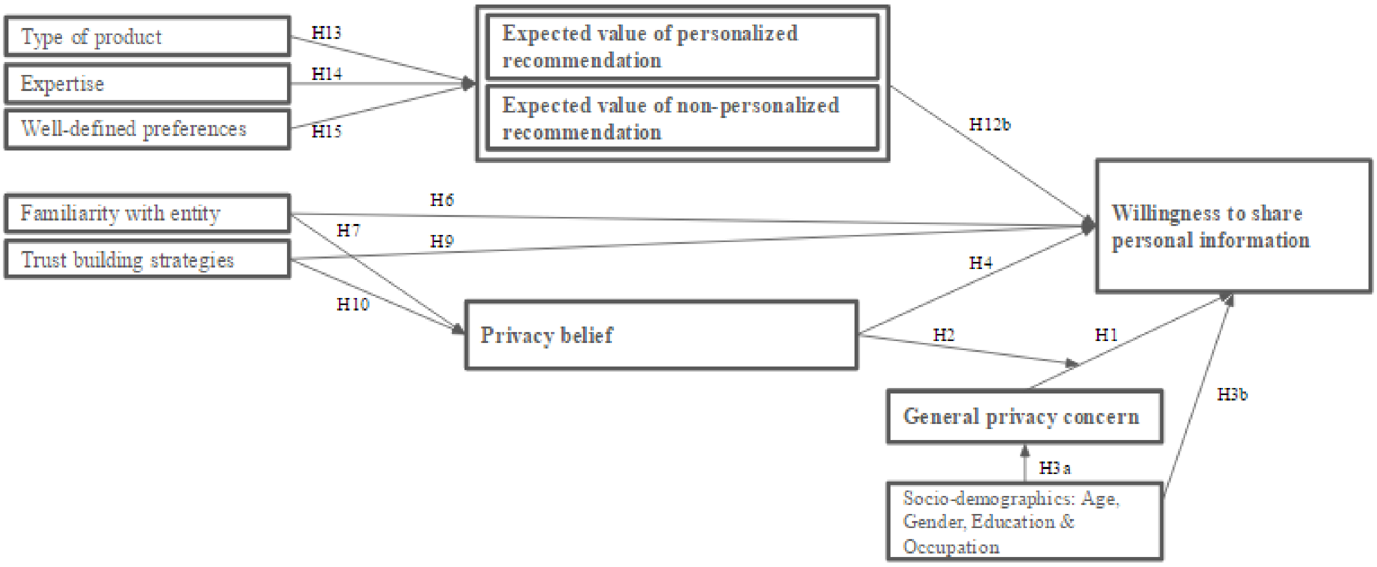



*Figure 1: Conceptual framework*

### *3.1 General privacy concern*

Li et al. (2008) have found a significant negative effect of privacy concern on privacy related behavioral intentions. Furthermore, research has also shown that a higher level of general privacy concern can lead to a decrease in consumer's willingness to partake in online profiling (Awad & Krishnan, 2006). Therefore, it is expected that general privacy concern will also have a negative effect on the willingness to share privacy sensitive information for a recommendation. Based on the theory of planned behavior, this effect is expected to be greater, the lower the privacy belief. However, in turn it is expected that privacy concern will also moderate the effect of privacy belief on the willingness to share privacy sensitive information.

> *H1: General privacy concern will have a negative effect on the willingness to share personal information.*
>
> *H2: The effect of general privacy concern on willingness to share will be moderated by privacy belief (The higher the privacy belief, the smaller the effect of general privacy concern on the willingness to share personal information).*

*Socio-demographics*

Awad & Krishnan (2006) found that the variables age, gender, education and income have effect on the willingness to be profiled online for personalized services. Milne and Rohm (2000) have suggested that older, female and less educated people are more concerned about threats to their personal privacy. Therefore, it may be expected that these people would be less willing to share their personal information. Additionally, research has found that consumers who have a high stimulation level prefer to take risks. When the environmental stimulation, determined by ambiguity, complexity and novelty, comes below optimum, an individual will try to increase the stimulation (Raju, 1980, p. 272). Sharing personal information can be seen as a risk people are willing to take to increase stimulation. Younger, more educated and employed people appear to have a higher optimum stimulation level. Therefore, it is expected that these people will be more likely to share privacy sensitive information.

> *H3a: Younger, female, more educated and employed people will have a lower general privacy concern.*
>
> *H3b: Younger, female, more educated and employed people will be more willing to share personal information.*

### *3.2 Privacy belief*

Chellapa and Sin (2005) found a significant effect of privacy concern on the likelihood of using personalization services. However, with privacy concern they mean whether the consumers believe their information is collected and treated fairly by a specific firm. This is referred to as privacy belief and since it is expected that the likelihood of using personalization services is related to the willingness to share privacy sensitive information for a personalized online recommendation, it is expected that privacy belief will also affect the willingness to share privacy sensitive information for a personalized online recommendation. Furthermore, Li et al. (2008) have also found a significant positive effect of privacy belief on privacy related behavioral intentions. Therefore, it is expected that privacy belief will have a positive effect on the willingness to share personal information. Based on the theory of planned behavior it is expected that general privacy concern and privacy belief strengthen each other’s effect on the willingness to share personal information. Similar to H2, it is expected that the effect of privacy belief will be greater, the higher the general privacy concern.

*H4: Privacy belief will have a positive effect on the willingness to share personal information.*

*H5 (cf. H2): General privacy concern will moderate the effect of privacy belief on the willingness to share personal information (The higher the general privacy concern, the smaller the positive effect of privacy belief on the willingness to share personal information).*

*3.2.1 Familiarity with entity*

According to Chellapa and Sin (2005) familiarity with the entity has a positive effect on the likelihood to use personalized services. Based on these findings it is also expected that familiarity with the entity will have a positive effect on the willingness to share personal information for a personalized online recommendation. Furthermore, Sheehan and Hoy (2002), found an effect of familiarity with the entity on privacy concern of the specific case (which is called privacy belief). This study will try to verify this finding and also test if privacy belief mediates the effect of familiarity on the willingness to share personal information.

*H6: Familiarity with the entity will have a positive effect on the willingness to share personal information.*

*H7: Familiarity with the entity will have a positive effect on the level of privacy belief.*

*H8: Privacy belief will mediate the effect of familiarity on the willingness to share personal information.*

*3.2.2 Trust-building strategies*

Chellapa & Sin (2005) have found a positive effect of trust-building factors on the likelihood of personalized services usage. Similarly, Aguirre et al. (2015) have found that trust-building strategies (transferring trust from a media context or signaling trust with certain cues) can offset the negative effect of covert information collection on the adoption of personalized online advertisements due to the feelings of vulnerability that consumers experience when firms undertake covert information collection strategies. Furthermore, research has shown that consumer's cue-based trust in online retailers is positively related to their willingness to provide personal information (Wang et al., 2004). This study will verify these findings and also test whether privacy belief plays a mediating role in the effect of trust-building strategies on willingness to share personal information.

*H9: Trust-building strategies will have a positive effect on the willingness to share personal information.*

*H10: Trust-building strategies will have a positive effect on the level of privacy belief.*

*H11: Privacy belief will mediate the effect of trust-building strategies on the willingness to share privacy sensitive information.*

### *3.3 Value of the recommendation*

*3.3.1 Expected added value of a personalized recommendation*

Research has shown that information sources offering personalized recommendations have a positive effect on the perceived usefulness of the recommendation service and have a greater propensity to be followed compared to non-personalized recommendations (Lee & Lee, 2009; Senecal & Nantel, 2004). Based on these results, it is expected that the type of recommendation will have an effect on the perceived expected value of the recommendation. Furthermore, it is expected that the expected added value of a personalized recommendation will have a positive effect on the willingness to share personal information for a personalized recommendation. This expectation is based on Awad and Krishnan's (2006) findings that consumers' willingness to share personal information depends on the trade-off between the perceived usefulness of the personal information sharing and the potential negative consequences. This is also in line with the findings of Chellapa and Sin (2005), which suggest that predicting consumers' usage of online personalization services as a trade-off between the perceived value of the personalization and the concern for privacy for a specific firm.

*H12a: A personalized recommendation will be valued more than a non-personalized recommendation.*

*H12b: The expected added value of a personalized vs. non-personalized recommendation will have a positive effect on the willingness to share personal information.*

*3.3.2 Type of product*

Research has shown that the perceived usefulness of a review is moderated by product type. The results of Sen and Lerman (2007) showed that readers were less likely to find negative reviews of hedonic products useful, compared to utilitarian products. Similarly, Xiao and Benbasat (2007) have also suggested that product type might influence the user's evaluation of recommender systems. Furthermore, Senecal and Nantel (2004) have found that recommendations for experience products are more followed than for search products.

Therefore, it is also expected that the type of product will have effect on the perceived expected value of the recommendation (H13a). Furthermore, research has found a significant moderating effect of product type on the effect of social presence and intention to reuse the recommender system (Choi, Lee, & Kim, 2011). The results showed a smaller effect for utilitarian products versus hedonic products. Similarly to these results, it is expected that the effect of type of recommendation on the expected value of the recommendation will be moderated by the type of product (H13b). More specifically, the expected positive effect of a personalized recommendation versus a non-personalized recommendation on the expected value of the recommendation (H12a), is expected to be greater for experience products than for search products.

> *H13a: Type of product will have effect on the expected value of the recommendation (Recommendations for experience products will be valued more than recommendations for search products).*
>
> *H13b: Type of product will moderate the effect of type of recommendation on the expected value of the recommendation (The expected added value of a personalized recommendation will be bigger for experience products than for search products).*

*3.3.3 Expertise and well-defined preferences*

Recommendations can help consumers in the decision process by reducing the difficulty associated with choosing between the alternatives and increasing the confidence associated with it (Fitzsimons & Lehmann, 2004). Lee and Lee (2009) found that recommendation systems allow individual consumers to determine the best alternatives with the least amount of effort and in this way overcoming the information overload problem. However, on the other hand some users may feel that their freedom to choose is restricted and threatened (Lee & Lee, 2009). Since, product recommendations, containing not too many or too similar products, are viewed as simplifying the decision process, it is speculated that under certain conditions recommendations will not be valued positively. Research has shown that the amount of product category knowledge is negatively related to the perceived ease of use and perceived usefulness of the decision tools (Kamis & Davern, 2004). Furthermore, research has shown that the effectiveness of recommendation strategies is affected by the degree to which customer preferences are developed (Simonson, 2005; Kwon et al., 2009). Therefore, it is expected that people with high expertise of the product or well-defined preferences do not perceive the decision process as complicated since they already know what they want and are therefore not looking for recommendations to simplify their decision process. Accordingly, they might feel that their freedom to choose is restricted when a recommendation is made. Consequently, it is expected that consumers with a high expertise or well-defined preferences will have a lower perceived value of the recommendation.

*H14a: The amount of expertise will have a negative effect on the expected value of the recommendation.*

*H15a: The amount of well-defined preferences will have a negative effect on the expected value of the recommendation.*

Furthermore, it has also been proposed that the amount of product expertise moderates the effects of recommendation agent type on the users' evaluations of the recommender agent (Xiao & Benbasat, 2007). Pereira (2000) found that users with a high level of product class knowledge had more positive affective reactions to content-filtering recommendation systems (recommendations based on product attributes the consumer likes) than the collaborative-filtering ones (recommendations based on the opinions of like-minded people). Based on these results, it is expected that a greater amount of expertise will result in a smaller effect of a personalized recommendation on the expected value of the recommendation.

*H14b: The amount of expertise will moderate the effect of type of recommendation on the expected value of the recommendation. (The expected added value of a personalized recommendation vs. a non-personalized recommendation will be smaller for people with higher expertise).*

Similarly, it is also expected that the effect of type of recommendation on the expected value of the recommendation will be smaller for a person with a higher degree of well-defined preferences. According to Simonson (2005, p. 34), there are two dimensions of consumer preferences: first the degree to which consumers have well-developed and stable preferences and second the consumer's self-insight into these preferences, including their perceptions of the clarity and stability of their preferences. Simonson (2005) has proposed that customers who know that they do not have well-developed preferences are most likely to be receptive to advice and assistance in defining their preferences and that customers who both have well-developed preferences and good preference insight are likely to be less dependent on marketers' recommendations. Furthermore, Kwon et al. (2009) found that customers who should and should not necessarily be personalized can be identified by understanding their preference development. Their results showed that a personalized recommendation is more effective for customers who have stable preferences than a non-personalized recommendation is and that personalized user-collaborative recommendations such as neighborhood-based collaborative filtering is more effective for customers who have poor self-insight than recommendations based on knowledge or expertise is (Kwon et al., 2009). Based on these results, it is expected that the level of preference development will moderate the effect of type of recommendation on the perceived value of the recommendation. More specifically, it is expected that a higher preference development will result in a smaller effect of type of recommendation on the expected value of the recommendation.

*H15b: The amount of well-defined preferences will moderate the effect of type of recommendation on the expected value of the recommendation (The expected added value of a personalized recommendation vs. a non-personalized recommendation will be smaller for people with a higher level of well-defined preferences).*

# 4 Methodology

This research is based on an empirical quantitative study, where the data is collected by means of a survey. The data will be used to test the hypotheses, which were drawn in the previous section. The level of analysis in this study consists of individuals. This study researches the influences of privacy concern, the value of the recommendation and privacy belief on the willingness to share personal information of individual men and women for personalized product recommendations.

The conceptual framework could be applicable for all companies selling products or services online. Marketers can use the data collected through this survey to increase their understanding of consumers' responses to personalized online recommendations and their privacy concerns involved. By taking the results of this research into account, marketers could increase their sales, brand loyalty and customer satisfaction by increasing consumers' willingness to share personal information.

## *4.1 Overall design*

The overall design used in this study is a survey. The data is collected using a self-completed questionnaire which allows the collection of standardized data from a sizeable population in a highly economical way, allowing easy comparison (Saunders, Lewis & Thornhill., 2012, p. 177). The questionnaire is developed and distributed online through the website Qualtrics (2016), which offers the possibility to use more interactive formats, randomization and to insert pictures.

### *4.1.1 The questionnaire*

In order to prevent errors and misunderstanding, the questionnaire was first pilot tested among five people. The questionnaire started with an introduction including a thank you message, the purpose of the study and a short description of the content of the questionnaire (See appendix C for a copy of the questionnaire). Attention was drawn to the presentation of scenarios and the respondents were asked to try to imagine themselves shopping for the indicated products as much as possible. However, to avoid sensitizing respondents to the research topic, and thereby inadvertently increasing privacy concerns, the purpose of the study was not revealed completely. Respondents were told that the study was about understanding consumers' responses to online product recommendations. After the introduction, some quick questions were asked to determine the suitability of the respondents participating in the study. Participants were asked to indicate their preference and expertise for each of the four products. Furthermore statements about the respondent's general privacy concern are presented and the familiarity with the well-known firms is checked. In order to make sure the respondents understood the purpose and value of personalized recommendations, a comprehensive explanation was given of the two types of recommendation strategies before the respondents were faced with the scenarios. Similar to previous research studying consumers' willingness to provide personal information for personalized- services or advertising, the central characteristic of the questionnaire is the presentation of four hypothetical scenarios (Awad & Krishnan, 2006). The four scenarios described a situation in which the participant had to imagine themselves shopping for a certain product and being offered product recommendations. For each of the four products, respondents are asked about their expected value of a personalized and non-personalized recommendation, their willingness to share their personal information (Facebook profile) for a personalized recommendation and their privacy belief. The questionnaire ends with questions about the participants' familiarity with the Facebook login approach, their Facebook usage, age, gender, education, and occupation.

Since people generally do not want to fill in a long questionnaire, the number of questions had to be kept to a minimum in order to maximize the response rate (Saunders et al., 2012, p. 178). As respondents had to answer the same questions about their expected value of the recommendations and their privacy belief for the four scenarios, it was decided not to have alternative forms or check questions for these items. Therefore the reliability of these questions could not be tested. Only for the general privacy concern it was possible to measure the internal consistency since a multi construct scale is used.

#### *4.1.2 Overview experiment*

Within the questionnaire a classical experiment is conducted, whereby the respondents are randomly assigned to either one of the following 4 experimental conditions:

A. *New companies + no trust-building strategy*
B. *New companies + trust-building strategy*
C. *Well-known companies + no trust-building strategy*
D. *Well-known companies + trust-building strategy*

A 2 x 2 x 4 experiment is conducted, by randomly assigning the participants of the questionnaire to one of the four conditions. Compared to having the participants assigned to all 16 scenarios, this design decreases the time needed to fill in the questionnaire and thereby maximizes the response rate (Saunders et al., 2012, p. 178). Besides keeping the amount of questions to a minimum, the random assignment of participant to one of the four treatment conditions also decreases the amount of learning- and boredom effects (Field, 2009, p. 17).

The first between-subjects factor was the familiarity manipulation. Respondents were presented to scenarios with one of the two types of websites: a well-known company, or a new, unfamiliar website. The second between-subjects factor was the trust-building manipulation. Subjects were either assigned to scenarios with trust-building or without trust-building. The last factor, a within-subjects factor, was the product manipulation. The respondents were all assigned to two search and two experience products for which both product types one product was associated with low preferences and expertise as well as one product associated with high preferences and expertise.

The use of the four conditions removes the possible effects of alternative explanations to the planned interventions and therefore eliminates threats to the internal validity (Saunders et al., 2012, p. 176). However, a limitation of this research design is the external validity (Saunders et al., 2012, p. 176). Hypothetical questions do not give the respondents incentive to truly reveal their attitudes such as their willingness to share personal information. Furthermore, the external validity also depends on the capability and the willingness of the respondents to really imagine themselves in the scenario. However, in order to improve the external validity the scenarios were endeavored to be in a realistic consumer context as much as possible. One way of doing this, was by using familiar, everyday products that most people can imagine themselves shopping for. Furthermore, the approach used to collect the respondents' personal information should also be familiar. Many firms use the Facebook login approach to collect their customers' personal information and provide personalized content (Facebook Login for Apps, 2016). Lastly, to improve the respondent's recognition, the scenarios include pictures of logos of the well-known firms as well as screenshots from the Facebook login screen.

### *4.1.2 Recommendation types*

In each scenario, respondents are asked to imagine themselves shopping for a certain product on a certain website. The website offers the participant a product recommendation to help the participant in finding the product he or she wants. In order to find the expected added value of a personalized recommendation, two types of recommendations are offered. Respondents are asked about their expected perceived value for both a non-personalized recommendation as well as a personalized recommendation. First of all a recommendation based on the opinions of a team of experts is offered, which is a typical non-personalized recommendation (Kwon et al., 2009; Senecal & Nantel, 2004). Secondly, the respondents are also offered a personalized recommendation based on collaborative filtering, which makes use of the known preferences of a group of users in order to make recommendations for new users (Su & Khoshgoftaar, 2009). More specifically, the participants are offered a personalized recommendation based on their Facebook profile. Research has shown that users in online social networks share similar interests with the social partners and that online social networks can have significant value as a useful information source for recommendations (Lee, 2013). Participants are asked to login with their Facebook profile and accordingly give the firm permission to access their personal data. The Facebook login method is a common approach used by firms to access their customers' info and to personalize the content in their apps or websites (Facebook Login for Apps, 2016).

#### *4.1.3 Product type manipulation*

Similar to previous research (Senecal & Nantel, 2004), the only within-subject factor was the product manipulation. All respondents were confronted with products from all four product categories. The following products for each product category were selected based on the results from a pretest (see table 1):

Table 1:
*Product type manipulations*

| | *High expertise/preferences* | *Low expertise/preferences* |
|---|---|---|
| *Experience product* | 1. Restaurant | 2. Wine |
| *Search product* | 3. Smartphone | 4. Digital camera |

*Pretest*: For each product class, subjects were asked whether products could either be evaluated: 1. before purchase; 2. mostly before purchase; 3. mostly after purchase; 4. only after purchase ($n$ = 22). Furthermore, the respondents were asked to specify their level of expertise and preferences for each product class (See appendix A for a copy of the pretest questionnaire).

Results of the pretest indicated that the restaurant (mean = 3.23, median = 3, mode = 3) and wine (mean = 3.18, median = 3, mode = 4) product classes were perceived most as experience products. The mobile phone (mean = 1.73, median = 2, mode 1) and digital camera (mean = 2.04, median = 2, mode = 2) product classes were perceived most as search products. The difference between the evaluations of the mobile phone and restaurant product classes ($t(21) = -11.77$, $p < .001$) as well as the difference between the evaluations of the digital camera and wine product classes ($t(21) = -9.51$, $p < .001$) were significant.

Furthermore, the respondents indicated to be most knowledgeable regarding the restaurant (mean = 3.23, median =3, mode = 3) and mobile phone product classes (mean = 2.83, median =3, mode = 3). For digital cameras (mean = 2, median = 2, mode = 2) and wine (mean = 2.23, median = 2, mode = 2) the respondents indicated to be less knowledgeable. The strongest preference was for mobile phones (mean = 3.55, median = 4, mode = 4) and for restaurants (mean = 2.86, median = 3, mode = 3). The respondents indicated to have the least amount of preferences for digital cameras (mean = 2.27, median = 2, mode = 2) and for wine (mean = 2.55, median = 3, mode = 3). The differences between the level of preferences between wine and restaurant was not significant ($t(21) = -.781$, $p > .05$), however the difference in the amount of expertise between wine and restaurant was significant ($t(21) = -4.06$, $p < .001$). Lastly, the differences between the search products were both significant for the level of preferences ($t(21) = -9.46$, $p < .001$) as well as the level of expertise ($t(21) = -9.72$, $p < .001$).

The results of the pretest and the subsequently chosen products for each product category are similar to previous research. The usage of wine and a dinner at a restaurant as experience products and mobile phones as search products has previously also been done by Senecal and Nantel (2004) and Bei et al. (2004). Furthermore, previous research has also used digital cameras as a product class with low preferences (Kramer, 2007).

### *4.1.4 Familiarity manipulation*

The pretest also tested the familiarity with multiple firms for the different product categories. The website manipulation is based on the fact that the respondents are familiar with the well-known companies used in half of the scenarios. Therefore, it is important to check for their familiarity. For each firm, the respondents were asked whether they are familiar with the website, have visited the website before or have shopped at the website before. Based on the results, for each product category the following firms are used in the website manipulation:

- *Wine: Gall & Gall*
- *Mobile phone: Bol.com*
- *Digital camera: Bol.com*
- *Restaurant: Iens.nl*

The results of the pretest showed that all respondents were familiar with Gall & Gall and Bol.com of which 95.5% has also indicated to have visited the website or store before ($n$ =

21). However not everybody was familiar with the website Iens.nl on which restaurants can be found. 22.7% of the respondents ($n$ = 5) had never heard of Iens.nl before. Therefore, the questionnaire will start by checking the respondents' familiarity with the firms. If a respondent indicates not to be familiar with one or more of the three companies, the respondent will not be randomly assigned to one of the four groups but only to group A or B which consists of the new firms.

#### *4.1.5 Trust-building manipulation*

Trust-building strategies can be implemented in the context of online recommendation services by means of signaling cues concerning the data collection and usage practices (Aguirre et al., 2015). Examples of signaling trustworthiness are privacy or security disclosures, seals of approval, and awards from neutral sources (Wang et al., 2004).

A privacy disclosure seemed to be most realistic and practically applicable to the setting of this study. The privacy disclosure is presented in the explanation of the personalized recommendation as well as in the Facebook login screen. In this screen respondents give the firm permission to access their Facebook profile after which a personalized product recommendation can be made (See appendix B for a copy of the trust-building manipulation used). The following privacy disclosure is chosen for the trust-building manipulation: *Please note that this information is for our use only – we do not disclose or share this information with any third parties.*

### ***4.2 Research sample***

The online questionnaire is distributed within the personal network of the researcher through social media platform Facebook as well as LinkedIn. In order to increase the response rate a small incentive was put in place. Respondents who finished the questionnaire were given the possibility to participate in a raffle to win a 10 euro gift card for a web shop of their choice. The sample size was strived to be as large as possible, because the larger the size, the closer its distribution will be to the normal distribution and thus the more robust it will be and the better the results can be generalized (Saunders et al., 2012, p. 265). The minimum requirement for the sample size was stated of at least 30 people for every category compared since statisticians have shown that a sample size of 30 or more will usually result in a sampling distribution for the means that is very close to a normal distribution (Saunders et al., 2012, pp. 265-266).

The questionnaire was launched at June 4th and closed at June 8th 2016. In total, 175 individuals participated in the survey. However, for the first two questions 7 participants indicated to not have a Facebook account or not have previously bought a product or service online and were therefore redirected to the end of the survey. Furthermore, some respondents (*n* = 5) finished the questionnaire in under 4 minutes and were excluded from the dataset since it is not considered plausible that these people were able to carefully read all the explanations and questions in less than 4 minutes. Accordingly, the data of in total 163 respondents is used in this study.

The women in this sample are highly overrepresented, of the respondents 32.5% (*n* = 53) is male and 67.5% is female (*n* = 110). The respondents' age ranged between 18 and 68 years old. The vast majority of the respondents are between 18 and 26 years old (54%, *n* = 88). Furthermore, the participants of this study are relatively high educated. Of the respondents, 76.7% (*n* = 125) is in possession of a Bachelor's or Master's degree. Lastly, 46% of the respondents is student (n = 75), 38% is employed (*n* = 62) versus 11,7% unemployed (*n* = 19). The respondents were evenly distributed among the four treatment groups, with at least 40 respondents in each treatment group. The respondents between treatment groups did not significantly differ in their socio-demographic profile ($F$age(3, 159) = 1.01, $F$gender(3, 159) = .54, $F$occupation(3, 159) = .51, $F$education(3 ,159) = 1.33; all p-values > .05).

### *4.3 Operationalization of constructs and variables*

The conceptual framework consists of different variables that need to be operationalized. The variables are operationalized by using different constructs and scales from previous research discussed in the literature review.

#### *4.3.1 Willingness to share personal information*

The willingness to share personal information is measured using a single item asking the participant to indicate how willing they are to provide their personal information to firms in return for a personalized recommendation. The measurement used in this study is similar to the measurements used in previous research to measure the willingness to share personal information (Awad & Krishnan, 2006; Li et al., 2008; Malhotra et al., 2004; Phelps et al., 2000). The response categories the participants could choose from were 7-point Likert-style rating items ranging from "definitely not" to "definitely would".

- *Given this hypothetical scenario, please specify the extent to which you would agree to provide your Facebook profile to this firm in return for a personalized product recommendation.*

*4.3.2 General privacy concern*

General privacy concern is about the individual's personality trait or general tendency to worry about information privacy (Li et al., 2008, p. 41). It is measured by the following three 7-point Likert-scaled items ranging from "strongly disagree" to "strongly agree". The first item is adapted from the two items Awad and Krishnan used to measure privacy concern (2006). Items 2 and 3 were taken from Malhotra et al.'s global information privacy concern scale (2004) as has previously been done to measure privacy concern (Li et al., 2008). The internal reliability of the scale is checked with Cronbach's Alpha and turned out to be sufficiently reliable (Cronbach's Alpha = .782).

- *I am concerned about threats to my personal privacy when using the Internet*
- *Compared to others, I am more sensitive about the way online companies handle my personal information*
- *To me, it is most important to keep my privacy intact from online companies*

*4.3.2 Privacy belief*

Privacy belief is about the subjective probability that consumers believe their private information is protected as expected by a specific online vendor (Li et al., 2008, p. 41). Privacy belief is measured using a single item, adapted from one of the six items Li et al. (2008) have used to measure privacy belief. The participants were asked to specify their agreement or disagreement on a 7-point likert-style rating for the following statement concerning their privacy belief for each vendor.

- *I am confident that I know all the parties who would collect information if I transact with this vendor*

*4.3.3 Familiarity with entity*

Respondents will be randomly assigned to scenarios with well-known firms or to new firms. For the new firms, the respondents will simply be asked to imagine themselves shopping for a product and being offered a recommendation by a new firm, they have not heard of before. However, for the scenarios consisting of familiar firms a real example is given of a well-known firm in each product category to decrease the imagination needed. To check for the familiarity of these firms the following 3 items are combined and included: whether the respondent is familiar with the firm (Chellapa & Sin, 2005), has visited the firm's website before (Li et al., 2008) and has previously purchased products from the firm (Chellapa & Sin, 2005).

- *For each company, please indicate your level of familiarity with the firm (1= never heard of the company before, 2= heard of the company before, 3= have visited the website before, 4= have purchased services or products before)*

*4.3.4 Perceived value of recommendation*

For each scenario the perceived value of the recommendation will be measured separately for a personalized recommendation and a non-personalized recommendation. The expected value for both types will be assessed by asking the respondents to specify their agreement or disagreement on one statement for both a personalized and a non-personalized recommendation. The statement used in this study is adopted from the construct Lee & Lee (2009) used to measure the perceived usefulness of recommendation systems and was modified to reflect this study context.

- *The recommendation would be helpful for me to purchase goods*

*4.3.5 Product expertise*

In order to assess respondents' expertise with the different product categories, respondents were asked to rate themselves on how knowledgeable they are regarding the products from each scenario (Fitzsimons & Lehman, 2004).

- *How knowledgeable do you rate yourself regarding regarding the following product categories? (1= not at all knowledgeable, 10= extremely knowledgeable)*

*4.3.6 Well-defined preferences*

The variable well-defined preferences is measured using a single item concerning the respondent's' self-insight into their preferences. The respondents were asked to indicate their agreement with whether they had a strong preference for a certain product or brand in each of the four product categories mentioned in the scenarios. The measurement used in this study is similar to the measurements used in previous research. For example, to measure the respondents understanding of their preferences, Kramer asked respondents to state their agreement with whether they had a clear sense of their preferences for PDAs (2007, p. 230).

- *I have a strong preference for a certain product or brand in this category.*

## 5 Results

In this section the results of the research are presented. The hypotheses are tested using GLM univariate analyses, repeated measures ANOVAs and simple linear regressions. Since for each respondent multiple measurements are conducted for the four different product categories and therefore independence between all observations cannot be assumed, a repeated measure ANOVA is used to test the effect of treatments on consumers' privacy belief and willingness to share as well as the effect of product type on the expected value of the recommendation. This is referred to as the wide format and is used to test hypotheses 6, 7, 9, 10 and 13.

However for hypothesis 4 the independent variable (privacy belief) was also a repeated measure. In this case a second approach is used which assumes the repeated responses make up multilevel data. That is, the outcome variable (expected value expert recommendation, expected value personalized recommendation, willingness to share and privacy belief) is a single variable and another variable is computed to indicate the scenario (product). Consequently, each subject has four rows of data. This is referred to as the long format. In total 163 participants performed four scenarios resulting in 652 observations. In order to be able to compare the effect of privacy belief, general privacy concern and expected added value as well as the interaction effect of privacy belief and general privacy concern on willingness to share personal information, the long format is also used to test hypotheses 1, 2, 4, 5 and 12b. Furthermore, for hypothesis 14 and 15 the independent variables (expertise and preferences respectively) were also a repeated measure. Therefore the long format is also used to find the effects of expertise (h14) and preferences (h15) on the expected value of a recommendation.

### *5.1 Effect of general privacy concern and privacy belief (H1, H4)*

In order to test the first hypothesis, a one-way ANOVA was carried out to compare the mean willingness to share values for people with different levels of general privacy concern. Respondents were split into three groups: low general privacy concern ($n$ = 224), moderate general privacy concern ($n$ = 192) and high levels of general privacy concern ($n$ = 236). One assumption of the ANOVA is that the dependent variable should be approximately normally distributed for each group of the independent variable. However, as assessed with the Shapiro-Wilk's test ($p < .01$) the willingness to share data was not normally distributed for the three levels of general privacy concern. Nonetheless, the test is run regardless because the one-way ANOVA is considered fairly robust to deviations from normality (Field, 2009, p.

155). Another assumption of the ANOVA is homogeneity of variance. In order to test if the variances in the different groups are equal, the Levene's statistic is used. Levene's test for willingness to share indicated equal variances ($F$ = 2.91, $p$ = .06).

The willingness to share personal information for a personalized recommendation decreased from the low level of privacy concern to the moderate level and from the moderate level to the high level (see table 2). The results of the ANOVA showed a significant difference between the mean values for people with different levels of general privacy concern ($F(2, 649) = 28.24$, $p < .001$). To determine where the significance exists a planned contrast is conducted between people with a high level of general privacy concern and people with a low level of general privacy concern. The results show that the people with high privacy concern were significantly less willing to share their personal information than people with low privacy concern ($t(649) = -7.32$, $p < .001$). Based on these results, hypothesis 1, stating that general privacy concern will have a negative effect on the willingness to share personal information, is supported.

Table 2:
*Means and standard deviations on the measure of willingness to share personal information as a function of three levels of general privacy concern*

| Privacy Concern | *Mean* | *Std. Deviation* |
|---|---|---|
| Low (n=224) | 3.29 | 1.72 |
| Moderate (n=192) | 2.48 | 1.51 |
| High (n=236) | 2.19 | 1.60 |
| Total (n=652) | 2.65 | 1.68 |

Furthermore, it was expected that the level of privacy belief will have a positive effect on the willingness to share personal information (H4). In order to test this hypothesis, a second one-way ANOVA is conducted to compare the mean willingness to share values for people with different levels of privacy belief. Similarly as before, the respondents were classified into three groups: low privacy belief ($n$ = 183), moderate privacy belief ($n$ = 296) and high privacy belief ($n$ = 173). The respondents with a low privacy belief indicated to strongly disagree with the statement: *I am confident that I know all the parties who would collect information if I transact with this vendor.* Respondents with a moderate privacy belief indicated to disagree or somewhat disagree with the statement while respondents with a high privacy concern neither agreed or disagreed with the statement or agreed with the statement. In order to test if the variances in the different groups are equal, the Levene statistic is used. Levene's test for willingness to share indicated a violation of the assumption of homogeneity of variance ($F$ = 21.468, $p < .01$). As assessed with the Shapiro-Wilk's test the willingness to share data did not seem to be normally distributed for the three levels of privacy belief ($p < .01$). However, even when the assumptions are broken, the F-test in ANOVA is considered a robust test (Field, 2009, p. 155.)

The willingness to share personal information for a personalized recommendation increased with each higher level of privacy belief (see table 3). The results of the ANOVA showed a significant difference between the mean values of willingness to share for people with different levels of privacy belief ($F(2, 649) = 91.17$, $p < .001$). Since equal variances are not assumed, Games-Howell post hoc tests are conducted to determine where the significance exists. The results show that the willingness to share personal information was significantly higher for people with a high level of privacy belief ($p < .001$) and people with a moderate level of privacy belief ($p < .001$) compared to people with low level of privacy belief. Furthermore, people with a high level of privacy belief were also significantly more willing to share their personal information compared to people with a moderate level of privacy belief ($p < .001$). The results of the contrast test showed that people with a high level of privacy belief had a significantly higher willingness to share their personal information compared to people with a low level of privacy belief ($t(318) = 13.18$, $p < .001$). Based on these results, hypothesis 4 is supported.

Table 3:

*Means and standard deviations on the measure of willingness to share personal information as a function of three levels of privacy belief*

| Privacy Belief | *Mean* | *Std. Deviation* |
|---|---|---|
| Low (n=183) | 1.60 | 1.29 |
| Moderate (n=296) | 2.67 | 1.46 |
| High (n=173) | 3.73 | 1.72 |
| Total (n=652) | 2.65 | 1.69 |

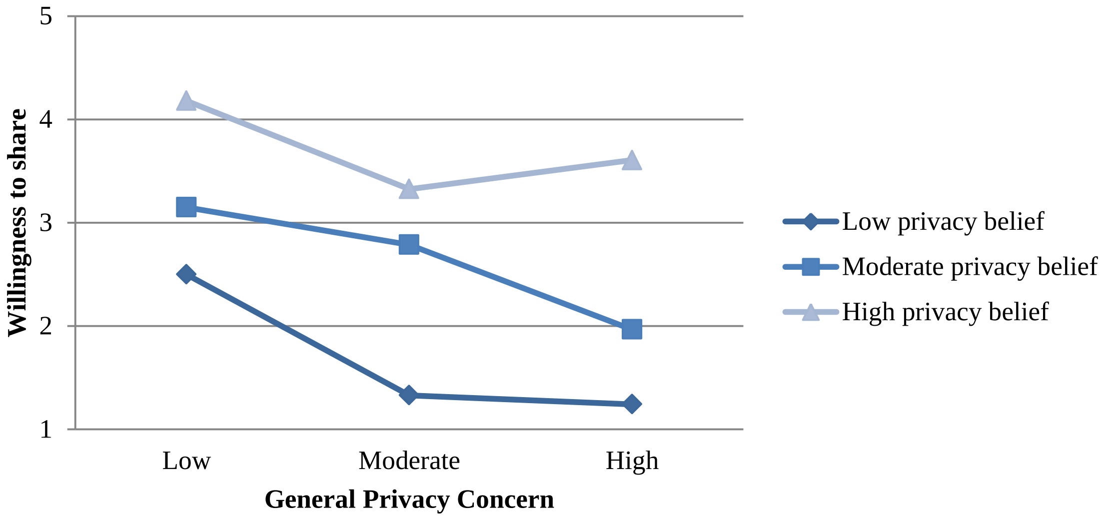
### *5.2 Interaction effect of general privacy concern and privacy belief (H2 cf. H5)*

Based on the theory of planned behavior, the negative effect of general privacy concern is expected to be smaller, the higher the privacy belief (H2). And in turn, it is expected that general privacy concern will also moderate the effect of privacy belief on the willingness to share privacy sensitive information (H5). In order to test these hypotheses, a two-way ANOVA is conducted.

The results show a significant interaction between the level of general privacy concern and privacy belief ($F(4, 643) = 3.57$, $p = .007$). Because the interaction effect was significant, the simple main effect of privacy belief is examined. That is, the differences between people with different levels of privacy belief for each of the three levels of general privacy concern. To control for Type I error across the simple main effects, a Bonferroni adjustment is applied. This means that the alpha level is set at .017 ($\alpha/3 = .05/3$). Looking at the significance values for each simple effect, it appears that there is a significant difference between people with different levels of privacy belief at all three levels of general privacy concern ($F$low(2, 643) = 20.03, $F$moderate(2, 643) = 28.87, $F$high(2, 643) = 51.36; all p-values < .001). Furthermore, the pair wise comparisons show that for people with a high level of privacy concern the effect of privacy belief is bigger than for people with a low level of privacy concern. Based on these results, hypothesis 5, stating that general privacy concern moderates the effect of privacy belief on consumers' willingness to share personal information for a personalized recommendation is supported.

Additionally, the simple main effect of general privacy concern is also examined. Looking at the significance values for each simple effect, it appears that there is a significant difference between people with different levels of general privacy concern at all three levels of privacy belief ($F$low(2, 643) = 13.13, $F$moderate(2, 643) = 18.10, $F$high(2, 643) = 5.19; all p-values < .01). More specifically, the pair wise comparisons show that people with a low level of privacy belief and a high level of general privacy concern had significantly lower willingness to share their personal information compared to people with a low level of privacy belief and a low level of general privacy concern ($p < .001$). However for people with a high privacy belief, no significant effect was found between people with a high or low level of privacy concern ($p = .07$). Indicating the effect of general privacy concern on consumers' willingness to share personal information is significantly greater for people with a low level privacy belief than for people with a high level of privacy belief. Based on these results hypothesis 2, stating that privacy belief moderates the effect of privacy concern on willingness to share, is accepted. The interaction effect of privacy belief and general privacy concern is visualized by plotting the estimated marginal means of willingness to share personal information for the levels of privacy belief and general privacy concern (see chart 1).

**Chart 1: Estimated marginal means of willingness to share personal information**




### *5.3 Effect of socio-demographics (H3ab)*

In order to test the effects of age, gender, occupation and education on willingness to share personal information, the wide format is used after computing the average willingness to share per respondent.

The results of a simple linear regression suggest that the respondent's age can significantly predict general privacy concern ($b$ = .03, $t$(161) = 3.82) as well as consumers' average willingness to share ($b$ = -.03, $t$(161) = -4.04). The respondent's age explains a significant proportion of variance in the level of general privacy concern ($R^2$ = .08, $F$(1, 161) = 14.57, $p$ < .001) and the level of consumers' average willingness to share personal information ($R^2$ = .09, $F$(1, 161) = 16.29, $p$ < .001). These results suggest that older respondents have more general privacy concern and are less willing to share personal information for a personalized online recommendation.

In order to compare the mean values of general privacy concern and average willingness to share between males and females a one-way ANOVA is conducted. The Levene's Statistic indicated equal variances in general privacy concern ($F$ = .44, $p$ = .51) and willingness to share ($F$ = 1.04, $p$ = .31) between males and females. The results of the ANOVA showed no significant difference between males and females in general privacy concern ($F$(1, 161) = .004, $p$ = .95) nor in average willingness to share ($F$(1, 161) = 1.99, $p$ = .16). Accordingly, gender does not seem to have effect on the level of general privacy concern or the willingness to share personal information for a personalized online recommendation.

It was expected that more educated people will have a lower general privacy concern and in turn will be more willing to provide personal information. Three levels of education were compared. The group of low educated respondents included people who finished a college (MBO), high school or less than high school degree ($n$ = 38). The moderate level of education consisted of people with a Bachelor's degree of a university of applied sciences ($n$ = 48) and the high level of education consisted of people with a Bachelor's or Master's degree from a university ($n$ = 77). The Levene's Statistic indicated equal variances among all three levels for both general privacy concern ($F$ = 2.37, $p$ = .10) as well as average willingness to share ($F$ = 1.17, $p$ = .31). However, the results of the ANOVA do not show significant differences in general privacy concern ($F$(1, 160) = 1.55, $p$ = .22) or average willingness to share ($F$(1, 160) = .23, $p$ = .79) between people with different levels of education. Accordingly, the results do not suggest that more educated people have a lower general privacy concern or are more willing to share personal information.

Lastly, the respondent's occupation was expected to have an impact on general privacy concern and average willingness to share. Three categories of occupation are identified; students, employed and unemployed (see table 4). The Levene's test indicated homogeneity of variances for average willingness to share ($F$ = 1.11, $p$ = .33), however for general privacy concern equal variances are not assumed ($F$ = 7.65, $p$ = .001). The results of the ANOVA showed a significant difference between the mean values of general privacy concern ($F$(2, 160) = 6.02, $p$ = .003) and average willingness to share ($F$(2, 169) = 6.11, $p$ = .003) for people with different occupations. To determine where the significance exists planned contrasts are conducted between unemployed and employed people and between students and non-students. The results suggest that students have significantly less general privacy concern ($t$(132, 83) = -1.05, $p$ = .004) and more willingness to share ($t$(160) = 1.71, $p$ = .001) compared to non-students. Furthermore, employed people had a significantly lower level of general privacy concern compared to unemployed people ($t$(65, 53) = -.83, $p$ = .004). However, no such significant difference was found in the willingness to share personal information between employed and unemployed ($t$(160) = .40, $p$ = .26).

Table 4:

*Means and standard deviations on the measures of general privacy concern and willingness to share personal information as a function of occupation*

| | General privacy Concern | | Willingness to share | |
|---|---|---|---|---|
| Occupation | *Mean* | *Std. Deviation* | *Mean* | *Std. Deviation* |
| Students (n=75) | 4.10 | 1.02 | 3.07 | 1.81 |
| Employed (n=62) | 4.20 | 1.48 | 2.34 | 1.54 |
| Unemployed (n=26) | 4.97 | 1.02 | 1.95 | 1.55 |
| Total (n=163) | 4.29 | 1.26 | 2.61 | 1.71 |

As stated in hypothesis 3a and 3b it was expected that younger, female, more educated and employed people will have a lower general privacy concern and in turn will be more willing to share personal information. However, a significant effect has only been found for age and occupation on general privacy concern and willingness to share. However, in contrary to what was expected employed people were not significantly more willing to share personal information compared to unemployed people. Accordingly, hypothesis 3a and 3b are partially supported.

### *5.4 Effect of familiarity and trust-building on willingness to share (H6, H9) and privacy belief (H7, H10)*

In order to test the effect of familiarity and trust-building on the degree of privacy belief and consumers' willingness to share personal information, the mean values of the four treatment groups are compared (see table 5). Since the respondents were asked about their privacy belief and willingness to share for four different products a relationship between the groups can be assumed. Accordingly, due to the lack of independence of observations two repeated measures ANOVAs are carried out to compare the willingness to share personal information values and privacy belief values of all four scenarios across the four treatment groups. That is, the within-subjects factor is product (smartphone, wine, restaurant and digital camera) and the two between-subjects factors are the trust building strategies (with or without) and familiarity of the firms (well-known firm or new firm).

As assessed by Shapiro-Wilk's test the willingness to share personal information was not normally distributed across each combination of the levels of the between- and within-subjects factors ($p < ,01$). However, ANOVAs are considered to be fairly robust to deviations from normality. If the sample sizes are not too small, even fairly skewed distributions might not be problematic (Field, 2009, p. 155). Mauchly's test of sphericity indicated that the assumption of sphericity had been slightly violated for the dependent variable willingness to share ($\chi 2(5) = 11.06$, $p = .05$). This means that the one-way repeated measures ANOVA is biased in that it too easily returns a statistically significant result. Therefore, a correction is made to correct for this bias by adjusting the degrees of freedom used in calculating the p-value. The results are interpreted using the Greenhouse-Geisser correction ($\varepsilon = .96$) and show significant differences in willingness to share for the four products ($F(2.88, 457.55) = 11.98$, $p < .001$) .

However, the results of the ANOVA showed no statistically significant difference in the willingness to share personal information between treatment groups with a trust-building strategy and without a trust-building strategy ($F(1, 159) = .06$, $p = .81$). Furthermore, no significant difference was found in willingness to share personal information between treatment groups with familiar firms or with new firms ($F(1, 159) = .84$, $p = .36$). Based on these results hypotheses 6 and 9, stating that familiarity with entity and trust-building strategies respectively will have a positive effect on the willingness to share personal information, are rejected.

Table 5:

*Means and standard deviations on the measures of privacy belief and willingness to share personal information as a function of treatment type*

| | Privacy belief | | Willingness to share | |
|---|---|---|---|---|
| Treatment | *Mean* | *Std. Deviation* | *Mean* | *Std. Deviation* |
| With trust-building (n=82) | 2.60 | 1.55 | 2.57 | 1.63 |
| Without trust-building (n=81) | 2.71 | 1.51 | 2.64 | 1.78 |
| Familiar firms (n=81) | 2.50 | 1.50 | 2.83 | 1.79 |
| New firms (n=82) | 2.80 | 1.55 | 2.39 | 1.60 |
| Total (n=163) | 2.66 | 1.52 | 2.61 | 1.71 |

In order to test the effects of treatments on privacy belief a second repeated measures ANOVA is carried out to compare the privacy belief mean values of all four scenarios across the treatment groups (see table 5). The results showed no statistically significant difference in privacy belief with or without a trust-building strategy ($F(1, 159) = 0.26$, $p = .61$). Furthermore, no significant difference was found in the level of privacy belief between treatment groups with familiar or with new firms ($F(1, 159) = 1.60$, $p = .21$). Accordingly, both hypothesis 7 and 10 are not supported.

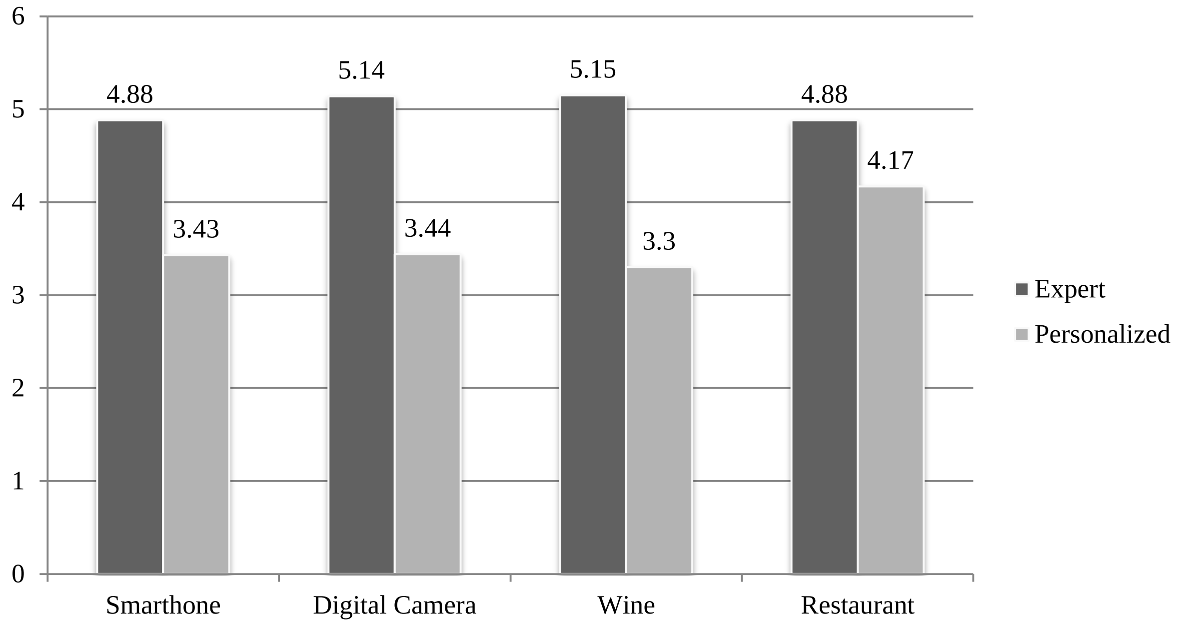
### *5.5 Mediating effect of privacy belief (H8, H11)*

As stated in hypothesis 8 and 11, it was expected that privacy belief mediates the effect of both familiarity and trust-building strategies on willingness to share. However, since hypothesis 6, 7, 9 and 10 were not accepted, mediation cannot exist. That is, according to Baron and Kenny, in order for the possibility of mediation to exist there has to be a significant effect of the predictor on the outcome variable, the predictor has to have a significant relationship with the mediator and the mediator should be significantly related with the outcome (1986) The results of this study did show a significant relationship between the mediator and the outcome (H4). However, this study did not find significant relations between either predictors on the outcome variable (H6, H9) or the predictors and the mediator (H7, H10). Accordingly, hypotheses 8 and 11 are not supported.

### *5.6 Effect of product type on expected value recommendations (H13)*

In order to test the effect of product type on the expected value of recommendations one-way repeated measures ANOVA procedures were conducted to compare the mean values of expert recommendations and personalized recommendations between the four products. Chart 1 visually presents the mean values of the expert and personalized recommendation for all four products. The wine ($M = 5.15$, $SD = 1.38$) and digital camera ($M = 5.14$, $SD = 1.47$) product categories had the highest expected value of expert recommendations, while the restaurant ($M = 4.17$, $SD = 1.84$) category had the highest expected value of personalized recommendations.

**Chart 2: Mean expected value recommendations**




As assessed with the Shapiro-Wilk’s test the dependent variables were not approximately normally distributed for each product category (all p-values < .01). Mauchly's test of sphericity indicated that the assumption of sphericity had not been violated for the data of personalized recommendations ($\chi 2(5) = 8.02$, $p = .16$). However for the value of expert recommendations, Mauchly's test of sphericity indicated that the assumption of sphericity had been violated ($\chi 2(5) = 13.14$, $p = .02$). Therefore the results of the ANOVA for the value of expert recommendations are interpreted using the Greenhouse-Geisser correction ($\varepsilon = .95$). The results show that the expected value of personalized recommendations ($F(3, 486) = 16.99$, $p < .001$) as well as of expert recommendations ($F(2.86, 463.84) = 3.10$, $p = .03$) are significantly different among the four product categories.

In order to test hypothesis 13a, stating that product type will have an effect on the expected value of the recommendations, follow up tests were conducted to test the difference between search products and experience products. The results showed that there was no significant difference in the expected value of expert recommendation between search products and experience products ($F(1, 162) = .001$, $p = .97$). However, personalized recommendations for search products were significantly valued less than for personalized recommendations for experience products ($F(1, 162) = 8.72$, $p = .004$). Based on these results hypothesis 13a is partially supported. The results show that personalized recommendations for experience products are valued more than personalized recommendations for search products. However, no such effect is found for expert recommendations.

In order to test hypothesis 13b, stating that type of product moderates the effect of type of recommendation on the expected value of the recommendation, a one-way repeated measures ANOVA was conducted on the added value of personalized recommendations data for the four different products. The added value of a personalized recommendation is calculated by subtracting the expected value of an expert recommendation from the expected value of a personalized recommendation. Mauchly's test of sphericity indicated that the assumption of sphericity had been violated ($\chi^2(5) = 18.89$, $p = .002$). Therefore, the results are interpreted using the Greenhouse-Geisser correction ($\varepsilon = .92$). The added value of personalized recommendations was significantly different among the four products ($F(2.77, 448.56) = 17.29$, $p < .001$). Furthermore, the follow up test showed that the added value of a personalized recommendation for search products was significantly lower than for experience products ($F(1, 162) = 5.38$, $p = .02$). Accordingly, hypothesis 13b is accepted.

### *5.7 Effect of added value on willingness to share (H12b)*

As stated in hypothesis 12b, the added value of a personalized recommendation is expected to have a positive effect on consumers' willingness to share personal information. The results of a simple linear regression suggest that the expected added value of a personalized recommendation significantly predicts the level of consumers' willingness to share their personal information ($b = .301$, $t(650) = 9.89$). The expected added value also explained a significant proportion of variance in the level of consumers' willingness to share personal information ($R^2 = .13$, $F(1, 650) = 97.86$, $p < .001$). These results suggest that the expected added value of personalized recommendation positively affects consumers' willingness to share personal information. Accordingly, hypothesis 12b is supported.

### *5.8 Effect of recommendation type on expected value (H12a)*

A one-way repeated measures ANOVA was conducted to determine whether there were statistically significant differences in the value of personalized recommendations compared to expert recommendations. The repeated measures design had been chosen because all respondents were asked to indicate their expected value for both a personalized and an expert recommendation. The expected values of both the personalized recommendation as well as the expert recommendation did not seem to be normally distributed as assessed with the Shapiro-Wilk's test ($p < .001$). However, as mentioned before the ANOVA is considered fairly robust to deviations from normality and therefore the test is run regardless. The results show that the expected value of a recommendation, is significantly different depending on the type of recommendation ($F$(1, 651) = 325.05, $p$ < .001). An expert recommendation ($M$ = 5.01, SD = 1.40) was valued significantly higher than a personalized recommendations ($M$ = 3.58), SD = 1.81). These results are in contrast to hypothesis 12a stating that personalized recommendations are more valued than expert recommendations. Accordingly, hypothesis 12a is rejected

Since the personalized recommendations are based on the respondent's Facebook profile, it may be expected that people who are more active on Facebook might expect higher values of their personalized recommendations. In order to test this a two way ANOVA is conducted with recommendation type as within-subjects factor and the level of Facebook activity as between-subjects factor. However, the interaction effect of Recommendation Type x Facebook Activity was not significant ($F$(3, 648) = 1.83, $p$ = .14). Accordingly, even when controlling for the level of Facebook activity hypothesis 12a is not supported.

### *5.9 Effect of expertise and preferences on expected value (H14, H15)*

It was expected that the effect of recommendation type on the expected value of the recommendation is moderated by expertise and preferences. More specifically, it was expected that the added value of personalized recommendations will be bigger for people with less expertise (14b) and less well-defined preferences (15b). In order to test these hypotheses the covariates expertise and preferences are included in the repeated measures ANOVA with recommendation type as within-subjects factor and expertise and preferences as covariates.

The results show a significant interaction between expertise and recommendation type ($F$(1, 649) = 12.13, $p$ = .001). In order to determine the difference between the effect of expertise on expert recommendations and on personalized recommendations, a simple linear regression is conducted for both recommendation types. The results show that expertise does have a significant effect on the expected value of personalized recommendations ($F$(1, 650) = 10.70, $p$ = .001), however in contrast to what was expected higher expertise is associated with a higher expected value of personalized recommendation ($b$ = .10, $t$(650) = 15.53, $p$ =.001). Furthermore, no significant effect was found on the expected value of expert recommendations ($F$(1, 650) = .34, $p$ = .54). Accordingly, hypothesis 14a, stating that the amount of expertise will have a negative effect on the expected value of the recommendation is not supported for both a personalized and an expert recommendation.

Furthermore, a simple linear regression established that expertise could statistically significantly predict the expected added value of a personalized recommendation ($b$ = ,12, *t*(650) = 3.32, $p$ = .001). Expertise also explained a significant proportion of variance in the expected added value of a personalized recommendation ($R^2$= .02, $F(1, 650)$ = 11.04, $p$ = .001). However, in contrary to what was expected, the results suggest that more expertise leads to a higher added value. Based on these results, hypothesis 14b stating that the added value of personalized recommendations will be smaller for people with higher expertise is rejected.

Furthermore, the results of the repeated measures ANOVA with within-subjects factor recommendation type and covariates expertise and preferences showed no significant interaction between the recommendation type and the level of well-defined preferences ($F(1, 649)$ = 1.47, $p$ = .23). Accordingly, hypothesis 15b stating that the level of well-defined preferences moderated the effect of type of recommendation on the expected value of the recommendation is not supported.

Since no significant interaction was found, the main effect of preferences on the value of a recommendation was examined. The test of between-subjects effects showed that there was no statistically significant difference in the expected value of a recommendation between different levels of preferences ($F(1, 649)$ = 2.31, $p$ = .13). Accordingly, hypothesis 15a, stating that the level of well-defined preferences will have a negative effect on the expected value of the recommendation, is not supported.

### *5.10 Summary*

In order to test the total effect of all independent variables on the dependent variable willingness to share personal information one last multiple regression analysis was performed. All independent variables from the conceptual framework that were expected to affect willingness to share information were included in the regression analysis. The model included the expected added value of personalized recommendations, trust-building, familiar firm, gender, age, education, occupation and privacy belief and general privacy concern. The results of previous analyses have shown a significant interaction effect between general privacy concern and privacy belief. Therefore, including only the two categorical variables in the model and thus only the main effects would not be accurate. Accordingly, in order to include the interaction effect of the two trichotomous variables general privacy concern and privacy belief, 8 dummy variables were included with D9 serving as the reference group (see table 6). Furthermore, for education the lower educated served as the reference group and for occupation the unemployed group.

Table 6:

*Dummy variables created in order to include the interaction effect between privacy belief and general privacy concern on willingness to share personal information*

| | Low privacy belief | Moderate privacy belief | High privacy belief |
|---|---|---|---|
| Low general privacy concern | D1 | D2 | D3 |
| Moderate general privacy concern | D4 | D5 | D6 |
| High general privacy concern | D7 | D8 | D9 |

The multiple regression model statistically significantly predicted willingness to share personal information ($F$(17,634) = 25.47 , $p$ < .001, adj. $R^2$ = .39). The regression coefficients and standard errors can be found in table 7. Similar as to the previous analyses, the variables trust-building, education and occupation did not add significantly to the prediction of willingness to share personal information. The variables expected added value of a personalized recommendation, familiar firm, age and gender did add significantly to the prediction (all p-values < .05). Noteworthy is that this regression analysis does show that the gender of the respondents can significantly add to the prediction of willingness to share. Previous analysis did not show significant differences between male and female respondents in their willingness to share personal information. Additionally, the familiarity manipulation also added significantly to the prediction while in the previous ANOVA no significant differences were found in the willingness to share between treatment groups with new firms or with familiar firms. This difference in results may be due to the long format of the data set used for the regression model while testing for the differences between the groups the wide format is used, therefore this analysis consisted of four times more data points compared to the wide format, which could have made marginally (in)significant results turn out to be significant. Accordingly, in the discussion the effects of gender and familiarity will be considered to be insignificant based on the previous ANOVAs using the wide format.

Furthermore, all variables concerning the general privacy concern and privacy, except the dummy variables D3 and D6, added statistically significantly to the prediction, $p$ < .05. Since D9 served as the reference group, the insignificant effect of D3 and D6 supports the interaction effect between privacy belief and general privacy concern. These results support hypothesis 2 which stated that privacy belief moderates the effect of general privacy concern on consumers' willingness to share personal information. More specifically, a high level of privacy belief seems to offset the effect of general privacy concern on willingness to share.

Table 7:

*Summary of regression analyses for variables predicting willingness to share personal information (N = 652 )*

| Variable | *B* | *SE B* | $\beta$ |
|---|---|---|---|
| Added Value | 0.21 | 0.03 | 0.26*** |
| Familiar firm | 0.48 | 0.12 | 0.14*** |
| Trust-building | -0.02 | 0.11 | -0.01 |
| D1 | -1.28 | 0.27 | -0.20*** |
| D2 | -0.49 | 0.22 | -0.11* |
| D3 | 0.21 | 0.25 | -0.04 |
| D4 | -2.23 | 0.25 | -0.37*** |
| D5 | -0.85 | 0.23 | -0.17*** |
| D6 | -0.47 | 0.26 | -0.07 |
| D7 | -1.88 | 0.23 | -0.36*** |
| D8 | -1.54 | 0.22 | -0.32*** |
| Age | -0.02 | 0.01 | -0.14** |
| Female | -0.36 | 0.12 | -0.10** |
| Student | 0.09 | 0.22 | 0.03 |
| Employed | -0.31 | 0.18 | -0.09 |
| Moderate Education | -0.04 | 0.16 | -0.01 |
| High Education | -0.22 | 0.14 | -0.06 |
| *Adjusted* $R^2$ | | 0.39 | |
| *F* | | 25.47*** | |

**p* < .05. ***p* < .01. ****p* < .001.

## 6 Discussion

In this section the findings of the study are discussed and compared to the literature and findings of previous research. Next, the theoretical and managerial implications are discussed. Lastly, the limitations of the study are discussed and suggestions for future research are made.

### *6.1 General discussion*

In this study the expected values of personalized and non-personalized recommendations are compared and the effects of consumers' privacy belief, general privacy concern and the expected added value of personalized recommendations on the willingness to share personal information for an online personalized recommendation are studied. These analyses served the purpose of providing a deeper insight into the effectiveness of online personalized recommendation.

In line with previous research, a significant negative effect of general privacy concern and a positive effect of privacy belief on consumers' willingness to share personal information is found (Li et al., 2008; Awad & Krishan, 2006; Chellapa & Sin, 2005). Furthermore, the findings of this study suggest that the effect of general privacy concern on willingness to share is moderated by the level of privacy belief. For people with a low level of privacy belief, a significant effect was found of general privacy concern on consumers' willingness to share personal information. However for people with high levels of privacy belief, no significant effect was found. This supports the theory of planned behavior study in such a way that the intention to share personal information depends on the combination of the subjective probability that consumers belief that their information will be treated fairly (privacy belief) and the evaluation of how big the damage would be if their information is treated unfairly (privacy concern). Only when there is both a high perceived chance as well as substantial consequences then and only then will there be a significant influence on the decision.

Besides the levels of general privacy concern and privacy belief, the willingness to share personal information also seemed to be dependent of the added value of a personalized recommendation compared to a non-personalized recommendation. This finding supports previous research that suggest consumers' willingness to share personal information partially depends on the perceived usefulness of the personal information sharing (Awad & Krishnan, 2006).

### *6.1.1 General privacy concern*

The results of this study show a negative effect of the respondents' age on their willingness to share personal information. This is in line with previous research that has suggested that older people are more concerned about threats to their personal privacy (Milne & Rohm, 2000). Due to a higher optimum stimulation level it was expected that younger, more educated and employed people were more likely to share personal information (Raju, 1980). As expected younger people seemed to have less general privacy concern compared with older people. However, no significant difference was found between female and male respondents nor between employed and unemployed respondents in willingness to share personal information. Furthermore, occupation did seem to have effect on general privacy concern but not on willingness to share personal information.

### *6.1.2 Privacy belief*

Previous research found a positive effect of familiarity with the entity on the likelihood to use personalized services (Chellapa & Sin, 2005) as well as on privacy belief (Sheehan & Hoy, 2000). Furthermore, trust-building factors also seemed to have a positive effect on the likelihood to use personalized services (Chellapa & Sin, 2005) and to provide personal information (Wang et al., 2004). Based on these findings it was expected that privacy belief would mediate the effect of familiarity and trust-building on willingness to share. However, in contrary to what was expected no significant differences were found in privacy belief or willingness to share between treatment groups with- or without trust-building and treatments groups with new firms of well-known firms.

Respondents in the treatment groups with trust-building strategy were presented the following privacy disclosure: *Please note that this information is for our use only – we do not disclose or share this information with any third parties.* However, no significant effect was found of the trust-building strategy on the respondent's privacy belief or willingness to share personal information. Alternatively, a second explanation could be that the respondents who faced the trust-building cue became aware of the possibility that their information could indeed be shared with third parties and thereby increasing the awareness and involvement which could have resulted in a backfiring effect if the cue was not perceived credible. This is in line with the elaboration likelihood model, which proposes that the amount of effort a person dedicates to processing a message depends on multiple variables in the persuasion situation (Petty & Cacioppo, 1986). When the elaboration likelihood is high, persuasion comes about through careful and thoughtful examination of the issue's relevant considerations. In contrast, when elaboration is relatively low, persuasion comes about through some simple decision rule to evaluate the message. In this case the non-significant effect of the trust-building cue used could be due to a higher degree of involvement due to the trust-building cue itself (context) or due to the customer's level of general privacy concern (Bansal, Zahedi, Gefen, 2008). Furthermore, research has suggested that privacy issues may not be addressed by merely posting a privacy-policy statement (Bansal et al., 2008). Individuals use multiple cues and variables to form their evaluations about how an online retailer may deal with their personal information. Accordingly, a possible explanation of this contradicting result could be that the manipulation was simply too small and respondents did not notice or pay enough attention to the cue or that factors in the context or in the respondent's level of general privacy concern may had a bigger effect. Therefore, for future research it may be interesting to further look into the differences and combinations of multiple trust-building cues and settings.

The second manipulation between the treatment groups was the use of well-known firms versus new firms. Respondents in the well-known firms treatment groups had indicated to be familiar with the well-known firms, such that they have heard of or have visited the website before or previously bought services or products from the online retailer. Based on the results of previous research, it was expected that familiarity with the entity would positively increase the respondents' privacy belief as well as their willingness to share personal information (Chellapa & Sin, 2005; Wang et al., 2004). However, no significant difference was found in the level of privacy belief or the willingness to share personal information between respondents in the treatment groups with well-known firms versus new firms. This contradicting result may be due to the methodology of this research. That is, the external validity of multiple measurements in this study are dependent on the capability and willingness of the respondents to really project themselves in the scenario. One explanation therefore could be that the respondents in the new firm treatment groups did not notice the fact that they arrived on a new website which they never had visited before or that they were not able to imagine or understand the meaning and consequences of this. Alternatively, the respondents could have also had negative associations with the familiar firms resulting in a lower privacy belief compared to the respondents in the new firms treatment groups.

Even though the differences between treatment groups in privacy belief and willingness to share did not seem to be significant, an interesting pattern can be seen in table 5. For familiar firms, the willingness to share personal information (M = 2.83) is higher than the privacy belief (M = 2.50). While in contrast, for new firms the privacy belief (M = 2.80) is higher than the willingness to share (M = 2.39). A possible explanation for this pattern might be that the well-known firms, compared to new firms, led to negative associations resulting in a lower privacy belief but nonetheless consumers might be more confident about the capabilities of the well-known firms in providing good personalized services. Therefore despite the lower privacy concern consumers may still be more willing to share their personal information for a personalized product recommendation due to a higher expected value of the personalized recommendation. This could be an interesting topic, future research could seek to further investigate.

*6.1.3 Expected added value of a personalized recommendation*

Previous research has shown that personalized recommendations have a positive effect on the perceived usefulness of the recommendation and have a greater propensity to be followed compared to non-personalized recommendations (Lee & Lee, 2009; Senecal & Nantel, 2004). However, in contrast to what was expected, was the expert recommendation significantly valued more than the personalized recommendation. This contradicting result may be due to some respondents not valuing the personalized recommendation as much as expected since they believe not much valuable information can be obtained from their Facebook profile. However, even when controlling for the level of Facebook activity, the expert recommendation was still valued more than the personalized recommendation. Therefore, this contradicting finding may also be the result of the personalization paradox. Research has shown that a greater personalization can lead to a rejection of personalized advertisements due to feelings of vulnerability which arise when consumers lack a sense of control over the situation (Aquirre et al., 2015). Alternatively, this contradicting result may also be due to respondents not completely understanding the purpose or believing in the possible value of personalized recommendations. Accordingly, for future research it may be suggested to use real examples of personalized recommendations to decrease the amount of imagination needed and in order for the respondents to truly understand it.

Besides the type of recommendation it was also expected that the type of product and the respondent's level of expertise and well-defined preferences would have effect on the expected value of the recommendation. In line with previous research, this study found a significant effect of product type on the perceived value of a personalized recommendation (Senecal & Nantel, 2004; Xiao & Benbasat, 2007). More specifically, personalized recommendations for experience products were valued more than recommendations for search products. However, for expert recommendations no such effect was found. This finding suggests that the effect of product type on the value of the recommendation may be moderated by the recommendation type. The respondents may have seen the expert recommendation for search products as a tool of acquiring full and objective information prior to the purchase. Therefore they may be just as relevant for search products as for experience products. However, personalized recommendations may not be perceived as relevant for search products as for experience products since consumers can acquire full information by inspection of the product prior to the purchase by themselves and thus a less complex decision process is involved and therefore a personal recommendation may not be perceived as relevant for search products as for experience products. Furthermore, the results of this study show that the expected added value of a personalized recommendation is significantly higher for experience products than for search products. This is in line with previous research, which has also found a moderating effect of product type although then on the effect of social presence on the re-usage of recommender systems (Choi et al., 2011).

Based on previous findings it was expected that people with high expertise of the product or well-defined preferences do not perceive the decision process as complicated since they already know what they want and are not looking for recommendation to simplify their decision process (Kamis & Davern, 2004; Lee & Lee, 2009, Fitzsimons & Lehman, 2004; Simonson, 2005; Kwon et al., 2009). Consequently, it was expected that consumers with high expertise or well-defined preferences will have a lower expected value of the recommendation. Furthermore it was expected that a greater amount of expertise or a higher level of well-defined preferences would result in a smaller effect of a personalized recommendation on the expected value of the recommendation. However, in contrast to what was expected, the results of this study showed a positive effect of expertise on the value of the recommendation and the level of well-defined preferences did not seem to have effect on the expected value of the recommendations. Similarly, the results did show a moderating effect of the level of expertise however this was also in the opposite direction of what was expected. Furthermore, for the level of well-defined preferences no moderating effect was found. This could be due to the fact that, unlike expected, the level of well-defined preferences did not have an effect on the expected value of a recommendation.

A possible explanation of the opposite effect of expertise may be that higher expertise is related to higher product involvement. With product involvement the personal relevance or importance of the product category is meant (Higie & Feick, 1989). Therefore, people with a higher level of expertise may have also had a higher involvement in a specific product category and were therefore more interested in recommendations for the products. This is in line with previous research that has shown a moderating effect of product involvement on the attitude toward recommendation mechanisms (Kwon & Chung, 2010). Similarly, people with low expertise in a certain product category may not have been interested in the product and consequently were not interested in any recommendations. Even though the scenario did state the participants to imagine themselves looking for the product, it could be that the respondents were not able to sufficiently imagine this and therefore indicated a lower expected value of the recommendation than may have been expected. Another explanation of the positive effect of expertise as well as the non-significant effect of preferences on the expected value may be the operationalization of the variables. In order to minimize the length of the questionnaire, only one question was used to assess the level of expertise, well-defined preferences and the value of the two recommendation types. Therefore the reliability of these constructs could not be checked.

### *6.2 Theoretical implications*

This study strengthens the lines of research that suggest effects of privacy belief and general privacy concern on consumer's willingness to share personal information of a personalized recommendation (Li et al., 2008; Awad & Krishan, 2006; Chellapa & Sin, 2005). Furthermore, this study also provides support for the theory that recommendations for experience products are valued differently compared to recommendations for search products. (Senecal & Nantel, 2004; Xiao & Benbasat, 2007). Lastly, the results of this study support previous research that suggest that the willingness to share personal information or to use recommender systems depends on the expected perceived value of the recommendation (Lee & Lee, 2009; Senecal & Nantel, 2004).

Besides supporting existing streams of research, this study also adds some new findings to the literature. The theory of planned behavior is applied to the context of decision-making in whether or not to provide personal information for a personalized recommendation. The results of this study show that the effect of general privacy concern on the decision to provide personal information depends on the level of privacy belief. More specifically, general privacy concern does not seem to have effect on the willingness to share personal information in cases of high privacy belief.

### *6.3 Managerial implications*

The findings of this study have practical implications for managers who sell products or services online. Marketers could use the findings of this study to increase their understanding of consumers’ responses to personalized online recommendations and their concerns for privacy involved. By taking the results of this research into account, marketers could increase their sales, brand loyalty and customer satisfaction by increasing consumers’ willingness to share personal information and offering personalized online product recommendations.

First of all, the results of the study emphasize the importance of privacy belief. Besides the direct positive effect of privacy belief on consumers’ willingness to share, the results of this study also show that a high level of privacy belief can offset the negative effect of general privacy concern on consumers’ willingness to share personal information. Therefore, managers would be well advised to reveal their (potential) customers level of privacy belief and to try to increase this where possible.

In order to increase privacy belief, caution should be taken when creating certain trust-building cues. Depending on the degree of involvement, consumers can take different routes to persuasion (Petty & Cacioppo, 1986). This involvement; the amount of effort a person dedicates to processing a message, may be dependent on the context and on the level of general privacy concern (Bansal et al., 2008). A trust-building cue itself may increase the involvement which could have a backfiring effect if the cue is not perceived credible, this however does need to be tested further. Therefore, it is important for marketers to assess the consumers’ perceived credibility and trustworthiness of the context including the website and any other cues involved in the online shopping environment.

Lastly, when offering online product recommendations it is recommended to take into account the product type. The results of this study supports previous research that suggest personalized recommendations for experience products are perceived more useful than for search products (Senecal & Nantel, 2004).

### *6.4 Limitations and suggestions for future research*

Even though the methodological decisions have been taken with great care and consideration, some limitations should be taken into account when interpreting the results. First of all due to the relatively young and relatively high educated research sample, caution should be taken in generalizing the results to the population of internet shoppers. Especially, since previous research has shown that female, older, and less educated people appear to have higher levels of privacy concern, it is important when studying the effects on consumers’ willingness to share personal information for a personalized recommendation, to obtain a highly representative sample (Milne & Rohm, 2000).

Furthermore, another limitation considering the research design of this study is the use of hypothetical shopping scenarios. As mentioned before the external validity of the constructs used in this study is dependent on the participants' capability and willingness to imagine themselves in the scenario shopping for a certain products. Furthermore, the hypothetical questions concerning the respondent's expected value of personalized recommendation, despite the comprehensive explanation of the personalization approach, may have also been difficult for respondents to assess. Therefore, for future research it is suggested to use real examples of personalized recommendations to decrease the amount of imagination needed.

In order to increase the response rate, the number of questions was kept to a minimum. This may have resulted in less reliable measures. Therefore, in order to increase the reliability, future research could use multiple-item scales to measure the degree of well-defined preferences, the value of the recommendation and privacy belief.

This study focused on the willingness to share personal information and thereby the effectiveness of online personalized recommendations. However other antecedents such as the amount of products and the similarity of the products recommended may also effect the effectiveness of online personalized recommendation (Gan & Jiang ,2013). Therefore, when studying the effectiveness of online personalized product recommendations it can be recommended to focus on more antecedents than merely consumers' willingness to share information. Furthermore, since this study showed some contradicting results in comparison to previous research, it seems that there are still some factors left to be analyzed in studying the willingness to share personal information for a personalized recommendation. One interesting topic, future research could seek to further investigate, is the effect of a person's level of expertise in a product category on the value of a product recommendation. As mentioned before this study found contradicting results in the effect of expertise on the expected value of a product recommendation. In contrast to what was expected this study found a positive effect of expertise on the expected value of a product recommendations. A possible explanation of the contradicting effect of expertise may be that higher expertise was related to higher product involvement, however this should be tested further.

Because of the importance of privacy belief, it may also be interesting for future research to further study the antecedents of privacy belief and analyze the possible strategies to increase this. Individuals use multiple cues and variables to form their evaluations about how an online retailer may deal with their personal information (Bansal et al., 2008). Therefore, multiple trust-building factors and different context settings may have different effects on the level of privacy belief and in turn on consumers' willingness to share personal information. One interesting topic, future research could focus on, is the application of the elaboration likelihood model on the use of trust-building cues to increase consumer's privacy belief and the relationship with.

Lastly, in order for the results to be more generalizable, future research could try to duplicate this research among a more heterogeneous sample group and include alternative product categories for the online personalized product recommendations. Furthermore, since research has shown that consumer's cultural surroundings or background may also influence online general privacy concern it may also be interesting to include and compare results from respondents with different cultures (Bandyopadhyah, 2006).

## 7 Conclusion

The aim of this study was to provide a deeper insight into the effectiveness of online personalized recommendations, by studying the influences of the expected added value of a personalized recommendation and the privacy-related concerns on consumer's willingness to share personal information. By means of an experiment within a self-administered questionnaire, the expected added value of a personalized recommendation, the consumer's general privacy concern and privacy belief are analyzed as well as their effects on consumers' willingness to share. Respondents were faced with four hypothetical shopping scenarios in which they had to imagine themselves shopping online for two types of products and being offered product recommendations. Furthermore, in order to test the effect of familiarity and trust-building strategies on the level of privacy belief and the willingness to share personal information, participants were randomly assigned to one of the four treatment groups.

The results of this study show that consumer's willingness to share personal information and thereby the effectiveness of online personalized recommendations depends on the expected added value of a personalized recommendation, the level of privacy belief and the level of general privacy concern. Furthermore, the results suggest that the negative effect of general privacy concern on the willingness to share can be offset by a high level of privacy belief. This emphasizes the importance for managers to reveal their customers level of privacy belief and to try to increase this where possible. However, caution should be taken when creating trust-building cues to increase privacy belief. Furthermore, in contrast to what was expected, the results of this study suggest that expert recommendations are significantly valued more than personalized recommendations. Furthermore, no significant effect was found of the trust-building and familiarity manipulation on privacy belief and willingness to share personal information for a personalized online product recommendation. Lastly, this study builds on previous research that suggest personalized recommendations for experience products are perceived more useful than for search products. More specifically the results of this study showed that the added value of a personalized recommendation for search products was significantly lower than for experience products.

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# Appendices

## *Appendix A: Pretest questionnaire*

Dear participant,

Thank you for participating in this survey. This survey is part of a pretest for my master thesis in Marketing. The survey will take approximately 3 minutes of your time and your answers are completely anonymous.

Kind regards,

Martine Ruigrok
MSc. Marketing student
Erasmus University Rotterdam

Click the button below to start the survey.

>>

For each of the following product categories, please indicate whether the product could either be evaluated 1. before purchase; 2. mostly before purchase; 3. mostly after purchase; or 4. only after purchase.

| | Product can be evaluated before purchase | Mostly before purchase | Mostly after purchase | Only the trial or usage of the product allows a product evaluation |
|---|---|---|---|---|
| Car insurance | | | | |
| Restaurant | | | | |
| Wine | | | | |
| TV programmes | | | | |
| Sport shoes | | | | |
| Mobile phones | | | | |
| News articles | | | | |
| Digital cameras | | | | |
| Fragrances (perfume) | | | | |

<< >>

Please indicate how knowledgeable you rate yourself regarding the following product categories:
1 = not at all knowledgeable; 4 = extremely knowledgeable

| | Not at all knowledgeable | | Extremely Knowledgeable | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| Car insurance | ○ | ○ | ○ | ○ |
| Restaurant | ○ | ○ | ○ | ○ |
| Wine | ○ | ○ | ○ | ○ |
| TV programmes | ○ | ○ | ○ | ○ |
| Sport shoes | ○ | ○ | ○ | ○ |
| Mobile phones | ○ | ○ | ○ | ○ |
| News articles | ○ | ○ | ○ | ○ |
| Digital cameras | ○ | ○ | ○ | ○ |
| Fragrances (perfume) | ○ | ○ | ○ | ○ |

<< >>

For each of the following product categories please indicate whether you have a strong preference for a certain product or brand in that category. (1= no preference; 4= very clear and strong preference for a certain product or brand)

| | No preference | | Very strong preference | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| Car insurance | ○ | ○ | ○ | ○ |
| Restaurant | ○ | ○ | ○ | ○ |
| Wine | ○ | ○ | ○ | ○ |
| TV programmes | ○ | ○ | ○ | ○ |
| Sport shoes | ○ | ○ | ○ | ○ |
| Mobile phones | ○ | ○ | ○ | ○ |
| News articles | ○ | ○ | ○ | ○ |
| Digital cameras | ○ | ○ | ○ | ○ |
| Fragrances (perfume) | ○ | ○ | ○ | ○ |

<< >>

For the following firms, please indicate whether you have heard of the company or have visited the website or store before.

| | Never heard of the company before | Have heard of the company before | Have visited the website or store before |
|---|---|---|---|
| lens.nl | ○ | ○ | ○ |
| Gall & Gall | ○ | ○ | ○ |
| Bol.com | ○ | ○ | ○ |
| Coolblue | ○ | ○ | ○ |
| Zalando | ○ | ○ | ○ |

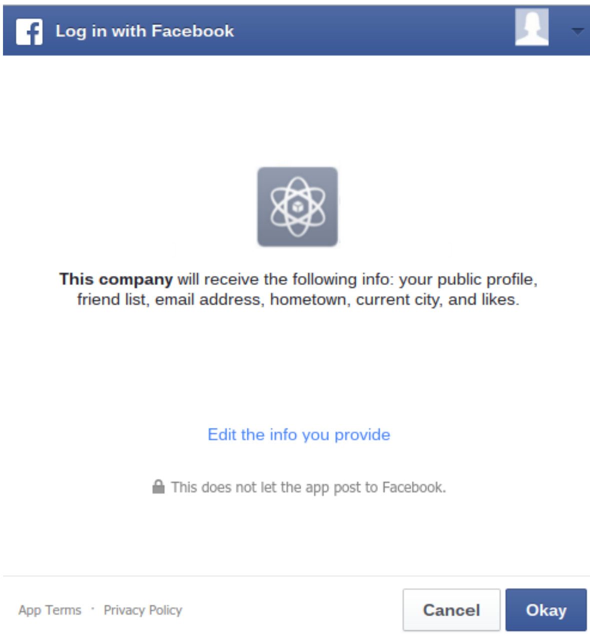
| | Never heard of the company before | Have heard of the company before | Have visited the website or store before |
|---|---|---|---|
| Ici Paris | ○ | ○ | ○ |
| Douglas | ○ | ○ | ○ |
| Uitzendinggemist.nl | ○ | ○ | ○ |
| Independer | ○ | ○ | ○ |
| Netflix | ○ | ○ | ○ |

| | Never heard of the company before | Have heard of the company before | Have visited the website or store before |
|---|---|---|---|
| Grapedistrict | ○ | ○ | ○ |
| Nu.nl | ○ | ○ | ○ |
| RTLnieuws.nl | ○ | ○ | ○ |
| MediaMarkt | ○ | ○ | ○ |
| PhoneHouse | ○ | ○ | ○ |

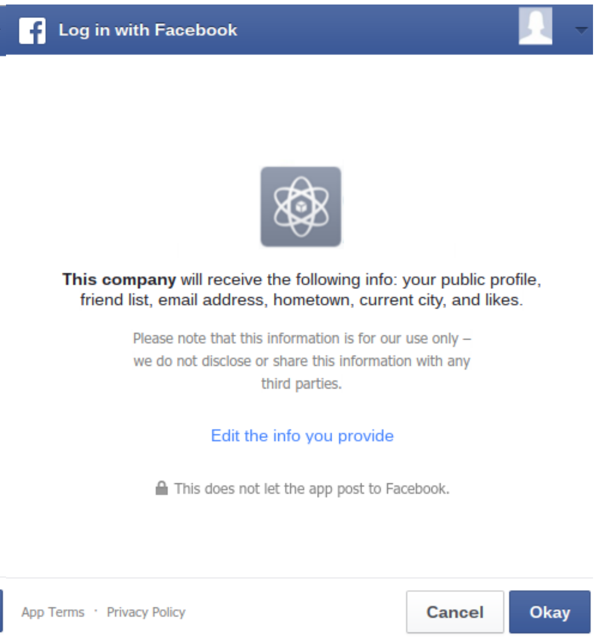
<< >>

## *Appendix B: Trust-building manipulation*

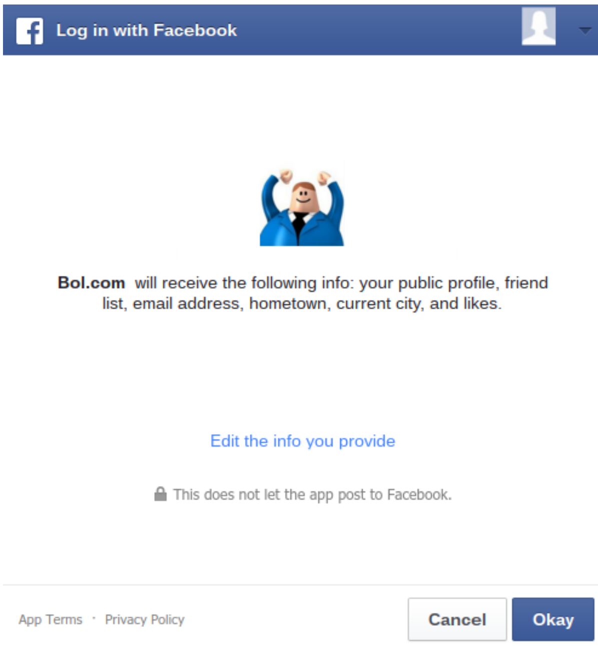
Treatment A



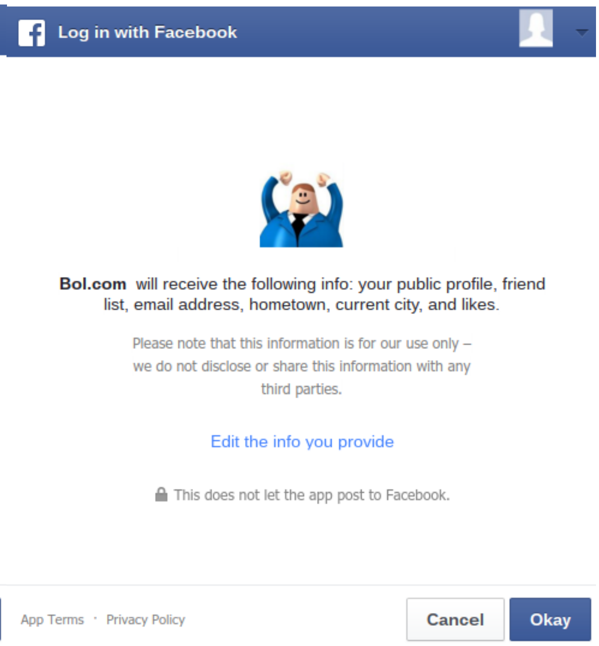

Treatment B




Treatment C




Treatment D



## *Appendix C: Questionnaire*

**Treatment group D:** Familiar firm with trust-building

**Scenario:** smartphone

Dear participant,

Thank you for helping me by participating in this survey. For my master's thesis in Marketing, I am conducting a study to understand consumers' responses to online product recommendations.
The survey consists of three parts. The first part contains a couple introductory questions. In the second part, **4 scenarios** will be presented, please try to imagine yourself shopping for the indicated product as much as possible. Lastly, you will be asked to answer some general and demographic questions.
The survey will take approximately **7 minutes** of your time and your responses are completely anonymous.
Participating in this survey gives you a chance at winning a €10-giftcard for an online shop of your choice if you leave behind your email address at the end of the survey.
Kind regards,
Martine Ruigrok
MSc. Economics & Business student
Erasmus University Rotterdam

Next

Do you have a Facebook profile?

Yes

No

Back Next

Have you ever purchased a good or service online?

Yes

No

Back Next

For each of the following companies, please indicate your level of familiarity with the firm.

| | Never heard of the company before | Have heard of the company before | Have visited the website before | Have previously purchased services or products before |
|---|---|---|---|---|
| Gall.nl (Gall & Gall) | O | O | O | O |
| Iens.nl | O | O | O | O |
| Bol.com | O | O | O | O |

Please indicate your level of agreement with the following statements:

| | Strongly disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly agree |
|---|---|---|---|---|---|---|---|
| I am concerned about threats to my personal privacy when using the internet | O | O | O | O | O | O | O |
| Compared to others, I am more sensitive about the way online companies handle my personal information | O | O | O | O | O | O | O |
| To me, it is most important to keep my privacy intact from online companies | O | O | O | O | O | O | O |

Please indicate your level of agreement with the following statements:

| | Strongly disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly agree |
|---|---|---|---|---|---|---|---|
| I have a strong preference for a specific type of smartphone or smartphone brand | O | O | O | O | O | O | O |
| I have a strong preference for a specific type of digital camera or digital camera brand | O | O | O | O | O | O | O |
| I have a strong preference for a specific bottle of wine or type of wine | O | O | O | O | O | O | O |
| I have a strong preference for a specific restaurant or type of restaurant | O | O | O | O | O | O | O |

Please indicate, on a scale from 1-10, how knowledgeable you rate yourself regarding the following product categories:

| | Not knowledgeable at all 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Extremely knowledgeable 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Smartphones | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Digital cameras | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Wine | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Restaurants | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

Back Next

In the following section, you will be presented with four scenarios. Each scenario is about the fictional purchase of a certain product and the influence of product recommendations on your decision.
Online product recommendations can help consumers with choosing between alternatives.
In this questionnaire two types of recommendation strategies are considered.
Please read through the following descriptions carefully, since it is important to understand how both types of recommendations work.

- First, non-personalized recommendation strategies can recommend products based on an evaluation by a team of **experts**.
- Second, **personalized** recommender systems use information about you, to find other people who are similar to you. It will then recommend products based on the behavior and preferences of people that are similar to you.

Back Next

**Scenario 1/4**
Imagine yourself **shopping for a new smartphone at Bol.com.** The company offers you help in finding the **smartphone** you want by offering you recommendations.
First of all it gives a recommendation from an **expert**.

*"This recommendation is based on an evaluation by our team of experts. Our advisers, experts in this product class, highly recommend this* ***smartphone*** *over the others."*

---

Please indicate your level of agreement with the following statement:

The expert recommendation would be helpful for me to purchase a new smartphone

| | | | | | | |
|---|---|---|---|---|---|---|
| Strongly disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly agree |

**Scenario 1/4**
Imagine yourself still **shopping for a new smartphone at Bol.com.**
Secondly the company can develop a **personalized recommendation** for you based on your social network profile. This information can be very useful for a company. Firms can learn about your lifestyle and psychographics and incorporate this into personalized marketing or services. Based on this data they can find out to which other customers you are most similar and accordingly make better suited recommendations specifically for you.

You will be asked to log in with your Facebook account. Based on your public Facebook profile, your friend list, email address, hometown, current city and your likes the company can make automatic predictions about your interests and suggest products that are most suited for you specifically. (Your public profile includes your name, profile picture, age range, gender, language, country and other public info)

*"This recommendation results from the analysis of your Facebook profile. Our computer system analyzed your profile and compared to other users and their preferences, the system highly recommends this* ***smartphone*** *over the others."*

bol.com

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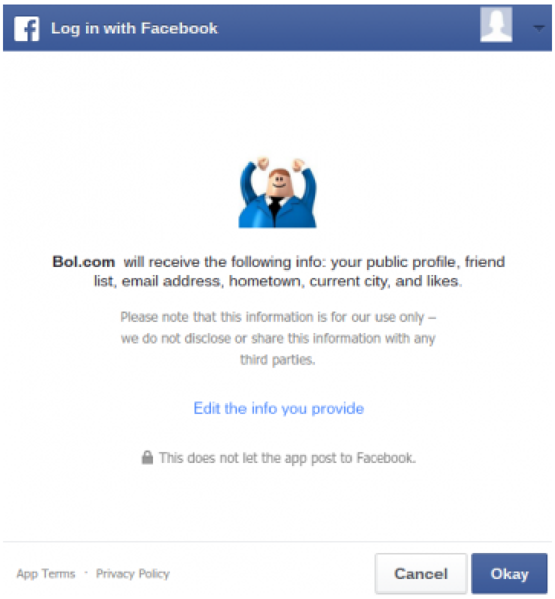
Please indicate your level of agreement with the following statement:

The personalized recommendation would be helpful for me to purchase a new smartphone

| | | | | | | |
|---|---|---|---|---|---|---|
| Strongly disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly agree |




Given this hypothetical scenario, please specify the extent to which you would agree to provide your Facebook profile to **Bol.com** in return for a personalized **smartphone** recommendation.

| Definitely not | Most probably not | Probably not | Might or might not | Probably | Most probably would | Definitely would |
|---|---|---|---|---|---|---|

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Please indicate your level of agreement with the following statement:

I am confident that I know all the parties who would collect information if I transact with Bol.com

| Strongly disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly agree |
|---|---|---|---|---|---|---|

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What is your gender?

- Male
- Female

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What is your age?

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What is your highest level of education completed?

- Less than high school
- High school (vmbo/mavo/mulo)
- High school (HAVO/VWO)
- College (MBO)
- University of Applied Science (HBO)
- University Bachelor degree (WO)
- University Master degree (WO)
- Doctorate (Phd)

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How often, if at all, do you post or browse on Facebook?

- Less than monthly
- Monthly
- Weekly
- Daily

How often do you use Facebook Login? For example to get (quick) access to a  website or app?

- Never
- Sometimes
- About half the time
- Most of the time
- Always

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What is your joint household income per year?

- Less than €10,000
- €10,000 - €19,999
- €20,000 - €29,999
- €30,000 - €39,999
- €40,000 - €49,999
- €50,000 - €59,999
- More than €60,000
- I'd rather not say

Next

Thank you for participating in this survey! Please enter your e-mail address below if you want to join the lottery to win a €10 giftcard. Your e-mail address will only be used for this lottery.

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Thank you very much for your time spent taking this survey.
Your response has been recorded.

For any questions or comments please do not hesitate to contact me at:
martine.ruigrok@gmail.com

Kind regards,
Martine Ruigrok

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