# Crossing the Line between Cool and Creepy – Non-Linearity of Personalization in Online Retailing

**Alena Bermes**
Heinrich-Heine-Universität Düsseldorf
**Maximilian Hartmann**
Heinrich-Heine-Universität Düsseldorf
**Sebastian Danckwerts**
Heinrich-Heine-Universität Düsseldorf

Cite as:
Bermes Alena, Hartmann Maximilian, Danckwerts Sebastian (2020), Crossing the Line between Cool and Creepy – Non-Linearity of Personalization in Online Retailing. *Proceedings of the European Marketing Academy*, 49th, (63392)

Paper from the 49th Annual EMAC Conference, Budapest, May 26-29, 2020.

EUROPEAN MARKETING ACADEMY

# Crossing the Line between Cool and Creepy – Non-Linearity of Personalization in Online Retailing

**Abstract:**

Against the background of immense product choice in ecommerce, online retailers use personalized product recommendations to assist consumers in product search and selection. The personalization is based on individual preferences which consumers perceive to be both useful and privacy invasive. Prior research has focused on linear effects a consumer's perceived personalization has on subsequent online purchase intention. By extending the privacy calculus, we aim to challenge this view. Our results indicate that perceived personalization initially has a positive influence on online purchase intention before this effect turns negative after a certain extent of personalization is reached. We thus identify the relationship as being non-linear and the risks as surpassing the benefits at some turning point. The findings have implications for researchers and practitioners because the degree of personalization should be described as an optimization instead of a maximization problem.

*Keywords: Personalized Product Recommendations, Non-Linearity, Privacy Calculus*

*Track: Digital Marketing or Social Media*

## 1. Introduction

With the rise of ecommerce, consumers today have access to huge product assortments and immense information availability about products (Reinartz, Wiegand, and Imschloss, 2019). Given the limited human information processing capacity, however, identifying products that meet one's needs is challenging. Therefore, many online retailers make use of recommendation systems to assist consumers in product search and selection (Wang, Qiu, Kim, and Benbasat, 2016). The recommendation systems provide personalized product recommendations based on inferred interests and preferences of individual consumers (Murthi & Sarkar, 2003). They simplify the consumers' decision making process by reducing the consumers' information overload and associated time costs (Arora et al., 2008; Bakos, 1997). Therein, the value of personalization to consumers stems from the enhanced convenience (Chellappa & Sin, 2005). Yet, notwithstanding these benefits personalized product recommendations can also evoke negative effects such as consumer privacy concerns (Aguirre, Roggeveen, Grewal, and Wetzels, 2016) or perceptions of intrusiveness (Martin & Murphy, 2017; Van Doorn & Hoekstra, 2013). This phenomenon is referred to as "personalization paradox" (Awad & Krishnan, 2006). The related influence of a consumer's perceived personalization on online purchase intention has been proven in various contexts (e.g. Tam & Ho, 2006). Most often research has found the impact of personalization to be either positive (Postma & Brokke, 2002) or negative (Yu & Cude, 2009), in any case linear.

However, if these positive and negative effects are brought together we posit that another argumentation seems plausible: Initially, personalization positively influences online purchase intention because it reduces the consumers' perceived complexity. Yet, when a certain degree of personalization is reached this effect is reversed as a feeling of intrusiveness surpasses the benefits. This differentiation would imply a non-linear effect in form of an inverted-U function, which could prove to be essential for online retailers to not uselessly maximize their degree of personalization. This research work consequently strives to challenge the argumentation of linear causalities in personalization research. More precisely, we seek to answer the following research questions (RQ):

**RQ 1:** *How does perceived personalization affect privacy concerns and perceived convenience, and subsequent online purchase intention?*

**RQ 2:** *Which type of relationship exists between perceived personalization and online purchase intention?*

## 2. Theoretical Background and Hypotheses Development

By using the privacy calculus theory (Culnan & Armstrong, 1999), we investigate the impact of consumers' perceived personalization in online retailing. Perceived personalization is defined as the perception that content is tailored to individuals based on knowledge about their preferences and behavior (Hagen, 1999). In this study we focus on personalized product recommendation which are one form of personalized content (Ying, Feinberg, and Wedel, 2006). The personalized product recommendations are generated by intelligent recommendation systems that collect web activities of users (Reinartz et al., 2018). While this process happens automatically (Kim, Lee, Shaw, Chang, and Nelson, 2001), the consumer is aware that it requires the analysis of personal data (Ying et al., 2006). Following the privacy calculus, consumers weigh costs and benefits of individualized recommendations accordingly before deciding to act (Chellappa & Sin, 2005). We extend the privacy calculus model by a non-linear argumentation logic pertaining to the impact of perceived personalization.

Humans only dispose of a limited information processing capacity (Kahnemann & Lovallo, 1993). Too many choices lead to a cognitive overload for consumers and, for instance, the withdrawal of a product search (Diehl, Kornish, and Lynch, 2003). Personalized product recommendations can serve as a cognitive relief (Sutanto, Palme, Tan, and Phang, 2013) by satisfying consumers' need for convenience (Chellappa & Sin, 2005). This benefit is amplified against the ever increasing choice possibilities and information opportunities in ecommerce (Broniarczyk & Griffin, 2014). Previous research has demonstrated that the increased convenience in turn enhances a consumer's online purchase intention (e.g. Chiang & Dholakia, 2003). We therefore hypothesize:

***H1 & H2.*** *Perceived personalization has a positive influence on perceived convenience (H1), which in turn has a positive influence on online purchase intention (H2).*

Personalization involves the collection and analysis of various types of personal information. It is infeasible to achieve without some loss of privacy (Chellapa & Sin, 2005). Personalized product recommendations evoke consumer privacy concerns since consumers are unable to understand the mechanics of personalization and how and by whom their personal information is used (Dolin et al., 2018). Such perceived risks in turn negatively influence behavioral intentions (Kroschke & Steiner, 2017). For instance, Castañeda and Montoro (2007) have demonstrated a negative effect of privacy concerns on online purchase intention. Thus, we assume:

***H3 & H4***. *Perceived personalization has a positive influence on privacy concerns (H3), which in turn has a negative influence on online purchase intention (H4).*

Based on empirical evidence we have hypothesized that consumers perceive personalization to be beneficial while they are simultaneously feeling threatened in their privacy. Next, we combine findings from previous research in order to establish a more differentiated understanding of the construct and its influence on online purchase intention. Concretely, we assume that perceived personalization exhibits a non-linear impact on behavioral intentions which looks as follows: At first, perceived personalization has a positive effect on online purchase intention as it improves a consumer's perceived convenience (Tam & Ho, 2006) and decision quality (Xiao & Benbasat, 2007). When a certain extent of personalization is reached, this effect turns negative because a greater concern for privacy surpasses the benefits. More specifically, perceptions of manipulation (Phelps, Nowak, and Ferrell, 2000), scariness (Dolin et al., 2018) or invasion and violation of social norms (Jackson, 2018) might arise. The resulting relationship between perceived personalization and online purchase intention would be expressed as an inverted-U function. We derive the following hypothesis:

***H5.*** *Perceived personalization initially has a positive influence on online purchase intention, before this influence turns negative after a certain extent of personalization is reached.*

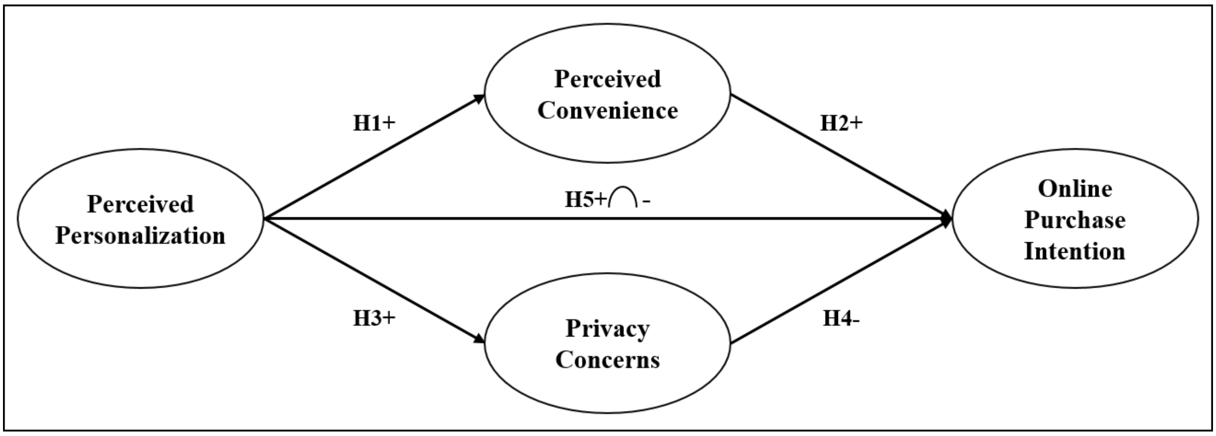


*Figure 1. Research Model*

## 3. Method

To test our hypotheses, we conducted an online survey in July 2019 with 278 participants (57% females, $M_{Age}$= 27) recruited mainly from social and professional network sites. We created a scenario of a hypothetical consumer decision-making process in which the respondents should imagine to currently be looking for a new laptop. The respondents were told to get a personalized recommendation for a laptop in a specific online shop based on their previous search history. Following the approach of Haas and Kenning (2014) we chose the leading German online retailer to maintain consistency. After presenting the scenario, we surveyed the model's constructs and control variables. For construct measurement we adapted established multi-item scales from previous research (Perceived Personalization: Tran, 2017; Privacy Concerns: Bleier & Eisenbeiss, 2015; Perceived Convenience: Noble, Griffith, and Adjei, 2006; Online Purchase Intention: Van der Hejden & Verhagen, 2004). All scales ranged from "strongly agree" (1) to "strongly disagree" (7).

To validate the measurement model, we tested construct reliability and validity. Table 1 shows that all Cronbach's Alpha values exceed the recommended level of 0.7 (Nunnally, 1978), that all average variances extracted (AVE) meet the 0.5 cutoff required (Fornell & Larcker, 1981) and that composite reliabilities for each construct are greater than the recommended threshold of 0.6 (Bagozzi & Yi, 1988). Furthermore, the square roots of the AVE for each construct exceed the interconstruct correlations, indicating discriminant validity (Fornell & Larcker, 1981). Overall, the confirmatory factor model fit the data well ($\chi^2/d.f.$=1.429; RMSEA=0.0390; SRMR=0.0361; GFI=0.958; AGFI=0.933; NFI=0.964; CFI=0.989). To test for potential common method bias Harman's one factor test was conducted (Podsakoff, MacKenzie, Lee, and Podsakoff, 2003). The results of this test reveal that common method bias does not pose a problem in our study.

| # | Construct | Factor Loadings | Cronbach's Alpha | Composite Reliability | AVE | Correlations/ Square Roots of AVE (bold) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | 1 | 2 | 3 | 4 |
| 1 | Perceived Personalization | .859-.880 | .832 | .900 | .751 | **.866** | | | |
| 2 | Privacy Concerns | .847-.915 | .917 | .942 | .802 | -.254 | **.895** | | |
| 3 | Perceived Convenience | .849-.849 | .743 | .888 | .799 | .092 | -.076 | **.894** | |
| 4 | Online Purchase Intention | .888-.919 | .921 | .945 | .811 | .263 | -.326 | .263 | **.901** |

*Table 1. Assessment of the measurement model*

**4. Results**

Hypotheses were tested via structural equation modelling with maximum likelihood estimation. The structural model (including its control variables, e.g. purchase frequency) shows a good model fit ($\chi^2/d.f.$=1.389; RMSEA=0.0370; SRMR=0.0478; GFI=0.957; AGFI=0.934; NFI=0.964; CFI=0.989). The findings indicate a positive effect of perceived personalization on perceived convenience ($\beta$=.14, $p$<.05). Additionally, perceived convenience has a positive effect on online purchase intention ($\beta$=.41, $p$<.001). We thus confirm H1 and H2. Surprisingly, perceived personalization does not influence privacy concerns positively but negatively ($\beta$=-.47, $p$<.001). We therefore cannot confirm H3. Yet, higher privacy concerns reduce online purchase intention, which confirms H4 ($\beta$=-.33, $p$<.001). Bootstrapping analysis using 5,000 samples (Hayes, 2013) further confirms that privacy concerns mediate the relationship between perceived personalization and online purchase intention (a×b = .112, 95% CI [.054, .198], $p$< .001) and that perceived convenience mediates the relationship between perceived personalization and online purchase intention (a×b = .044, 95% CI [.001 .130], $p$<.05).

To provide evidence for H5 we perform a quadratic regression analysis by regressing online purchase intention on perceived personalization and its square ($Y=\beta_0+\beta_1X+\beta_2X^2$). An inverted-U shaped relationship requires that the coefficient on X be positive and that of $X^2$ be negative (Haans, Pieters, and He, 2016). In our model the coefficients are of expected signs and significant. Perceived personalization initially has a positive effect on online purchase intention (*$\beta$=.91, $p$<.01*), yet, as of a certain degree this influence turns negative (*$\beta$=-.66, $p$<.05*). Therefore, the relationship between perceived personalization and online purchase intention can be described as non-linear. We thus confirm H5.

## 5. Discussion and Implications

The purpose of our study was to provide a differentiated understanding of the influence of perceived personalization on online purchase intention. Therein, our research makes several contributions to personalization literature. First and most importantly, we extend knowledge by reconsidering the influence of perceived personalization on online purchase intention. To the best of our knowledge, no study has investigated the non-linear impact of perceived personalization yet. Our results indicate that personalization initially has a positive influence on online purchase intention before this effect turns negative after a certain extent of personalization is reached. The degree of personalization should therefore be described as an optimization instead of a maximization problem. Online retailers need to identify the optimal degree of personalization for their product recommendations and not the highest possible. More concretely, to maximize online purchase intention retailers should analyze (and implement accordingly) which consumers prefer which degree of personalization to only just feel maximum convenience and no risk.

Second, our results seem to confirm earlier findings that consumers perform a risk-benefit analysis with regards to personalization and that perceived convenience increases online purchase intention while privacy concerns decrease it. However, we did not find a positive effect between perceived personalization and privacy concerns but a negative one. One explanation could be that we chose a scenario approach in which the consumers were aware that their information is being collected for personalization purposes. According to Milne, Bahl, and Rohm (2008) consumers' express fewer negative reactions with this type of overt personalization whereas covert personalization causes customers to feel as if they have lost control. Also, Komiak & Benbasat (2006) have shown that personalization increases trust. Therefore, it seems reasonable that personalization can also decrease privacy concerns.

Third, our study indicates that personalization research should go beyond the common risk assessments when studying behavioral intentions to personalized product recommendations, in particular given their inverted-U shaped relationship. Personalization definitely causes negative perceptions as of a certain extent. Yet, instead of privacy concerns other latent constructs may be responsible for these perceptions of risk. Against the background of increasing "datafication" (Lycett, 2013) Simonson (2015) has also called for the questioning of established theories. The integration of emotions could serve as a starting point (Kehr, Kowatsch, Wentzel, and Fleisch, 2015). Previous research has mainly relied on cognitive constructs to grasps the risks of personalization (Tucker, 2012). Yet, Jackson (2018) provides initial proof that personalization makes consumers feel "creepy". Constructs like a consumer's perceived vulnerability could account for the risk component within the personalization paradox (Aguirre, Mahr, Grewal, de Ruyter, and Wetzels, 2015; Martin & Murphy, 2017).

## 6. Limitations and Future Research

The relevance of the research topic and the study's key findings call for more research to shed light on how to effectively influence consumers' online purchase intention by the optimal degree of personalization. We aim to replicate the results in different cultures (this study was conducted in Germany) and with representative samples (e.g. accounting for gender, age or digital experience). Moreover, we aim to re-examine the calculus underlying the inverted-U function. Concretely, we are working towards integrating affective constructs such as perceived vulnerability into the privacy paradox. Further, although in line with Haas and Kenning (2014), the impact of perceived personalization may differ between different online retailers as well as product categories. Thus, the scope of this study should be extended accordingly. In this paper, we measured consumers' behavioral intentions (in line with other studies, e.g. Keith, Babb, Furner, and Abdullat, 2010). Yet, while intentions are a good predictor of actual behavior (Ajzen, 1991) measuring them does not allow to predict the threshold level at which consumers perceive personalization to be too strong. Future research should investigate this based on field studies.

In sum, we provide important insights regarding consumers' perception of personalization. Researchers and practitioners, i.e. online retailers and marketers, should focus on identifying the optimal degree of personalized product recommendations to not cross the line between the perception of coolness… or creepiness.

**References**


Aguirre, E., Mahr, D., Grewal, D., de Ruyter, K., & Wetzels, M. (2015). Unraveling the personalization paradox: The effect of information collection and trustbuilding strategies on online advertisement effectiveness. *Journal of Retailing*, 91(1), 34-49.

Aguirre, E., Roggeveen, A.L., Grewal, D., & Wetzels, M. (2016). The personalization-privacy paradox: Implications for new media. *Journal of Consumer Marketing*, 33, 98-110.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179-211

Arora, N., Dreze, X., Ghose, A., Hess, J. D., Iyengar, R., Jing, B., Joshi, Y. Kumar, V., Lurie, N. Neslin, S., Sajeesh, S. Su, M., Syam, N., Thomas, J., Zhang, J., Scott, N., & Sajeesh, S. (2008). Putting one-to-one marketing to work: Personalization, customization, and choice. *Marketing Letters*, 19(3-4), 305.

Awad, N.F., & Krishnan, M.S. (2006). The personalization privacy paradox: An empirical evaluation of information transparency and the willingness to be profiled online for personalization. *MIS Quarterly*, 30(1), 13-28.

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science*, 16(1), 74–94.

Bakos, J. Y. (1997). Reducing buyer search costs: Implications for electronic marketplaces. *Management Science*, 43(12), 1676-1692.

Bleier, A., & Eisenbeiss, M. (2015). The importance of trust for personalized online advertising. *Journal of Retailing*, 91(3), 390-409.

Broniarczyk, S. M., & Griffin, J. G. (2014). Decision difficulty in the age of consumer empowerment. *Journal of Consumer Psychology*, 24(4), 608-625.

Castañeda, J.A., & Montoro, F.J. (2007). The effect of internet general privacy concerns on customer behavior. *Electronic Commerce Research*, 7(2), 117-141.

Chellappa, R.K., & Sin, R.G (2005). Personalization versus privacy: An empirical examination of the online consumer's dilemma. *Information Technology and Management*, 6(2-3), 181-202.

Chiang, K. P., & Dholakia, R. R. (2003). Factors driving consumer intention to shop online: an empirical investigation. *Journal of Consumer Psychology*, 13(1), 177-183.

Culnan, M.J., & Armstrong (1999). Information privacy concerns, procedural fairness, and impersonal trust: An empirical investigation. *Organization Science*, 10(1), 104-115.

Diehl, K., Kornish, L.J., & Lynch, J.G. (2003). Smart agents: When lower search costs for quality information increase price sensitivity. *Journal of Consumer Research*, 30(1), 56-71.

Dolin, C., Weinshel, B., Shan, S., Hahn, C. M., Choi, E., Mazurek, M. L., & Ur, B. (2018). Unpacking perceptions of data-driven inferences underlying online targeting and personalization. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (p. 493). ACM.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50.

Haans, R. F., Pieters, C., & He, Z. L. (2016). Thinking about U: Theorizing and testing U-and inverted U-shaped relationships in strategy research. *Strategic Management Journal*, 37(7), 1177-1195.

Haas, A., & Kenning, P. (2014). Utilitarian and hedonic motivators of shoppers' decisions to consult with salespeople. *Journal of Retailing*, 90(3), 428-441.

Hagen, P., Manning, H., & Souza, R. (1999). Smart personalization. *Forrester Research*, Cambridge, MA.

Jackson, J. R. (2018). A perfect fit: Personalization versus privacy. *Journal of Organizational Psychology*, 18(4), 33-34.

Kahnemann, D., & Lovallo, D. (1993). Timid choices and bold forecasts: A cognitive perspective on risk taking. *Management Science*, 50(8), 1120-1133.

Kim, J. W., Lee, B. H., Shaw, M. J., Chang, H. L., & Nelson, M. (2001). Application of decision-tree induction techniques to personalized advertisements on internet storefronts. *International Journal of Electronic Commerce*, 5(3), 45-62.

Keith, M. J., Babb Jr, J. S., Furner, C. P., & Abdullat, A. (2010). Privacy Assurance and Network Effects in the Adoption of Location-Based Services: an iPhone Experiment. *ICIS*, 237

Kehr, F., Kowatsch, T., Wentzel, D., Fleisch, E. (2015). Blissfully ignorant: The effects of general privacy concerns, general institutional trust, and affect in the privacy calculus. *Information Systems Journal*, 25(6), 607-635.

Komiak, S. Y., & Benbasat, I. (2006). The effects of personalization and familiarity on trust and adoption of recommendation agents. *MIS Quarterly*, 941-960.

Kroschke, M., & Steiner, M. (2017). The influence of social cues on users’ information disclosure intentions – the case of mobile apps. *Proceedings of the 38th International Conference on Information Systems, Seoul, South Korea*, 1-17.

Lycett, M. (2013). ‘Datafication’: Making sense of (big) data in a complex world. *European Journal of Information Systems*, 22(4), 381-386.

Martin, K. D., & Murphy, P. E. (2017). The role of data privacy in marketing. *Journal of the Academy of Marketing Science*, 45(2), 135-155.

Milne, G. R., Bahl, S., & Rohm, A. (2008). Toward a framework for assessing covert marketing practices. *Journal of Public Policy & Marketing*, 27(1), 57-62.

Murthi, B.P.S., & Sarkar, S. (2003). The role of the management sciences in research on personalization. *Management Science*, 49(10), 1344-1362.

Noble, S. M., Griffith, D. A., & Adjei, M. T. (2006). Drivers of local merchant loyalty: Understanding the influence of gender and shopping motives. *Journal of Retailing*, 82(3), 177-188.

Nunnally, J. C. (1978). *Psychometric Theory*. New York, NY: McGraw Hill.

Phelps, J., Nowak, G., & Ferrell, E. (2000). Privacy concerns and consumer willingness to provide personal information. *Journal of Public Policy & Marketing*, 19(1), 27-41.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Ysychology*, 88(5), 879.

Postma, O. J., & Brokke, M. (2002). Personalization in practice: The proven effects of personalisation. *Journal of Database Management*, 9(2), 137–142.

Reinartz, W., Wiegand, N., & Imschloss, M. (2019). The impact of digital transformation on the retailing value chain. *International Journal of Research in Marketing,* 36(3), 350-366.

Simonson, I. (2015). Mission (largely) accomplished: What's next for consumer BDT-JDM Researchers? *Journal of Marketing Behavior*, 15, 9-35.

Sutanto, J., Palme, E., Tan, C. H., & Phang, C. W. (2013). Addressing the personalization-privacy paradox: An empirical assessment from a field experiment on smartphone users. *MIS Quarterly*, 34(4), 1141-1164.

Tam, K.Y., & Ho, S.Y. (2005). Web personalization as a persuasion strategy: An elaboration likelihood model perspective. *Information Systems Research*, 16(3), 271-291.

Tran, T. P. (2017). Personalized ads on facebook: An effective marketing tool for online marketers. *Journal of Retailing and Consumer Services*, 39, 230-242.

Tucker, C. (2012). The economics of advertising and privacy. *International Journal of Industrial Organization*, 30(3), 326-329.

Van Doorn, J., & Hoekstra, J. C. (2013). Customization of online advertising: The role of intrusiveness. *Marketing Letters*, 24(4), 339-351.

Van der Heijden, H., & Verhagen, T. (2004). Online store image: conceptual foundations and empirical measurement. *Information & Management*, 41(5), 609-617.

Wang, W., Qiu, L., Kim, D., & Benbasat, I. (2016). Effects of rational and social appeals of online recommendation agents on cognition-and affect-based trust. *Decision Support Systems*, 86, 48-60.

Xiao, B., & Benbasat, I. (2007). E-commerce product recommendation agents: Use, characteristics, and impact. *MIS Quarterly*, 31(1), 137-209.

Ying, Y., Feinberg, F., & Wedel, M. (2006). Leveraging missing ratings to improve online recommendation systems. *Journal of Marketing Research*, 43(3), 355-365.

Yu, J., & Cude, B. (2009). 'Hello, Mrs. Sarah Jones! We recommend this product!' Consumers' perceptions about personalized advertising: Comparisons across advertisements delivered via three different types of media. *International Journal of Consumer Studies*, 33(4), 503-514.