Social Dynamics Oscillating Between The Real And Virtual World

Predicting Consumer Choices and Company Profitability from Field Experiments and Computational Simulation Models

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St. Gallen, March 2012 Christian Hildebrand

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Summary

Social interactions with others are a fundamental part of our lives as they influence what brands we like, which products we buy, which emotions we experience while shopping, and also impact our future consumption intentions. However, interactions with others are not limited to the real world; they increasingly oscillate between the real and the virtual world. This dissertation is based on four articles providing empirical evidence how such interactions influence consumers' deviation from initial preferences, how these deviations affect consumers' satisfaction with final products, how those interactions in turn affect consumers themselves, and how companies may design such web-based systems to increase profitability.

In the first article, we examined how community feedback affects consumer self-designs in mass customization systems. In such systems, consumers have the possibility to use a computer-aided toolkit to self-design a product according to one's personal preferences. One of the central assumptions in previous research is that these systems allow consumers to self-design *unique* products that closely match their idiosyncratic preferences. However, we provide evidence from a field experiment in a car manufacturer's brand community that consumers receiving feedback on initial car designs assimilate toward external feedback, leading them to systematically choose *less unique*, more average car designs. Three follow-up lab experiments in a self-developed product customizer reveal additional evidence that, although consumers deviate from initial preferences in a predictable way, such deviations rather decrease than increase consumers' ultimate satisfaction. Implications for consumer welfare of such socially enriched mass customization systems are discussed, and the effects on manufacturer profitability based on additional Monte Carlo simulations are provided.

The second article reveals additional process evidence from two field experiments in our self-developed product customizer that receiving feedback on initial self-designs results in lower decision certainty, which in turn negatively affects individual purchase probability. Furthermore, we show that community feedback may not only systematically affect choices, but also negatively affects individual self-perceptions such that perceiving strong differences in one's personal design compared to what others have chosen led to lower self-esteem evaluations.

Opening up the process to show how such virtual interactions in online communities oscillate between the real and the virtual world, the third article examines how including Facebook comments on public displays in a retail store affect brand perceptions and sales. Based on a field experiment in the retail industry and complementary customer interviews, we show that although consumers perceive brands that utilize such social network comments as more innovative and attractive, consumers have a strong preference to see the comments of their friends but not their own. This creates a notable give-and-take paradox for using such social media strategies between the real and virtual world. Finally, we provide evidence that including social media comments translate into measurable effects on sales.

Since such online social networking sites, brand communities and manufacturer mass customization systems generate a vast amount of data, it is difficult to analytically derive closed-form solutions for making reasonable predictions. Apart from the attractive Bayesian modeling approaches in recent years to account for such heterogeneity and temporal dynamics, a new computational simulation method called Agent-Based Simulation Models (ABM) received considerable interest. This new methodology allows to simulate system behavior such as the diffusion of new products based on micro level data (e.g., individual preferences, risk perceptions, social susceptibility), as well as macro level data (e.g., information on the structure of the social network). However, recent debates emerged on how to rigorously build, test, and validate such models. In the final article, I review recent applications and accentuate the current lack of general standards to build, test and validate ABMs. The article provides a framework of guidelines on how to conduct ABM rigorously, and illustrates the use of these guidelines with an example for modeling viral marketing campaigns in social networks.

Zusammenfassung

Soziale Interaktionen haben einen wesentlichen Einfluss auf die von Konsumenten präferierten Marken, ihre Kaufentscheidungen, auf die empfundenen Emotionen während des Kaufprozesses sowie zukünftige Konsumabsichten. Gleichwohl beschränken sich diese Interaktionen nicht nur auf die reale Welt, sondern befinden sich vielmehr im Wechselspiel zwischen realer und virtueller Welt. Die vorliegende Dissertation zeigt im Rahmen von vier Artikeln den Einfluss solcher Interaktionen auf das Abweichungsverhalten initialer Konsumentenpräferenzen, wie diese Abweichungen die von Konsumenten empfundene Produktzufriedenheit beeinflusst sowie in der Folge die Wahrnehmung des Konsumenten selbst prägt. Zusätzlich geben die vorliegenden Studien Anhaltspunkte für die betriebliche Praxis, um die Profitabilität in einem solchen interaktionsgeprägten Kontext positiv zu beeinflussen.

Im Rahmen des ersten Artikels untersuchen wir dabei im Besonderen den Einfluss von Community Feedback auf die Gestaltung von individuell gestaltbaren Produkten in sog. Mass Customization Systemen. Innerhalb jener Systeme erhalten Konsumenten die Möglichkeit auf der Basis einer Applikation ein personalisiertes Produkt gemäss ihren persönlichen Präferenzen zu gestalten. Eine zentrale Annahme früherer Forschungsarbeiten hinsichtlich der Vorteile jener Systeme ist die Übersetzung idiosynkratischer Präferenzen in eine *einzigartige* Produktgestaltung auf Konsumentenseite. Im Rahmen eines Feldexperiments innerhalb der Brand Community eines führenden europäischen Automobilherstellers zeigen wir jedoch auf, dass Kunden mit ihren finalen Design-Entscheidungen systematisch in die Richtung des erhaltenen Feedbacks konvergieren und somit in der Folge *weniger einzigartige* sondern systematisch stärker dem Durchschnittsdesign angenäherte Designs entwickeln. Auf der Basis von drei Folgestudien innerhalb eines selbstentwickelten Produktkonfigurators zeigen wir, dass jene vorhersagbaren Abweichungen von initialen Präferenzen zur Abnahme der finalen Produktzufriedenheit führt. Die Folge jener Effekte sowohl hinsichtlich möglicher Wohlfahrtsbeeinträchtigungen aus Konsumentensicht, als auch der Profitabilitätssteigerung aus Unternehmenssicht auf Basis sich anschliessender Monte Carlo Simulationen werden aufgezeigt.

Im Rahmen des zweiten Artikels beleuchten wir die prozessualen Aspekte des Entscheidungsprozesses innerhalb jener feedback-basierten Mass Customization Systeme. Zwei Experimente innerhalb unseres entwickelten Produktkonfigurators

zeigen systematisch auf, dass jenes Abweichungsverhalten von initialen Präferenzen in die Richtung des Community Feedbacks die individuelle Präferenzsicherheit von Konsumenten vermindert und in der Folge negativ auf die Kaufwahrscheinlichkeit des finalen Produkts rekurriert. Überdies belegt dieser zweite Artikel den negativen Einfluss von abweichendem Community Feedback auf Selbstwahrnehmungsprozesse von Konsumenten. Wir zeigen bspw. auf, dass systematisch abweichendes Community Feedback zu einer verminderten Evaluation des eigenen Selbstwertes führt.

Der dritte Artikel öffnet den Betrachtungsrahmen in die Richtung einer verstärkten Verzahnung zwischen realer und virtueller Welt. Wir gehen der Frage nach, welchen Einfluss Facebook Kommentare auf sog. Public Displays auf Markenwahrnehmung und Umsatz im Einzelhandel ausübt. Auf der Basis eines Feldexperiments sowie weiteren Kundeninterviews belegen wir den positiven Einfluss jener Kommentare auf die wahrgenommene Innovativität und Attraktivität von Marken. Gleichwohl zeigen wir auf, dass Konsumenten eine verstärkte Präferenz aufweisen die Kommentare ihrer Freunde, nicht jedoch die Eigenen, lesen zu wollen. Darüber hinaus belegen wir den positiven Zusammenhang jener Social Media Kommentare und der Umsatzentwicklung der Marke.

Jene betrachteten sozialen Netzwerke, Brand Communities und Mass Customization Systeme produzieren eine Fülle komplexer Datenstrukturen und in der Folge die Herausforderung, jene Komplexität in Vorhersagemodellen adäquat abzubilden. Neben den attraktiven Modellen zur Abbildung zeitlicher Dynamik und Heterogenität auf Individualebene im Bereich der bayesianischen Statistik, entwickelten sich sog. agentenbasierte Simulationsmodelle (ABM) innerhalb der vergangenen Jahre. Trotz der attraktiven Eigenschaften zur Modellierung von Mikroinformationen (bspw. individuelle Konsumentenpräferenzen, Risikowahrnehmung, Ausmass an sozialer Beeinflussbarkeit) und Makroinformationen (bspw. Informationen über die Zusammensetzung eines sozialen Netzwerks), ergaben sich verstärkte Diskussionen zur adäquaten Entwicklung, des Tests und der Validierung jener Modelle. Im Rahmen des letzten Artikels wird die Abwesenheit eindeutiger Richtlinien anhand von aktuellen Publikationen in führenden wissenschaftlichen Zeitschriften innerhalb der Informationswissenschaften belegt. Auf der Basis dieser Analysen wird ein System von Richtlinien zur Entwicklung, des Tests und der Validierung von ABMs herausgearbeitet und anhand eines Beispiels zur Modellierung von viralen Marketingkampagnen in sozialen Netzwerken aufgezeigt.

Article I

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Product Customization in a Social Context: Community Feedback Stifles Creativity and Reduces Satisfaction with Self-Designed Products

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Abstract

Enabling consumers to self-design unique products that match their idiosyncratic preferences is the key value driver of modern mass customization systems. These systems are increasingly becoming "social," allowing for consumer-to-consumer interactions such as commenting on each other's self-designed products. The present research examines how receiving others' feedback on initial product configurations affects consumers' ultimate product designs and their satisfaction with these self-designed products. Evidence from a field study in a European car manufacturer's brand community and from three experiments show that receiving feedback on initial self-designs stifles consumers' creativity—i.e., they ultimately select self-designed products that are less unique—and causes them to be less satisfied with their self-designed products. The results also reveal that the negative influence of feedback on consumers' product satisfaction is mediated by an increase in decision uncertainty and perceived process complexity. The implications of socially enriched mass customization systems for both seller profitability and consumer welfare are discussed.

Keywords: Mass Customization Systems, User Self-Design, Product Configurators, Consumer Decision Making, Social Influence, Field Study, Experiment.

1. Introduction

Many companies in various industries provide mass customization (MC) systems that offer consumers the opportunity to self-design individualized products. Past research has shed light on how such systems of co-production through consumers' interaction with the vendor's customer interface facilitate the creation of products that closely match consumers' idiosyncratic preferences (e.g., Franke, Keinz, and Steger 2009; Dellaert and Stremersch 2005) and shown that the key driver of customer value from MC systems is consumers' opportunity to express their uniqueness and individuality (Franke and Schreier 2008). Against the background of a fast-growing demand for individualization, MC has become both a key tool for enhancing customer-firm interaction in marketing practice and an important area of research (Randall, Terwiesch, and Ulrich 2007; Syam, Ruan, and Hess 2005).

At the same time consumers increasingly use social media to exchange information about products, and many companies aim to harness social media technologies to foster sales and obtain consumer input to inspire the development of new products. Indeed, entire industries are being transformed from a command-and-control to a connect-and-coordinate mindset (Agarwal, Gupta, and Kraut 2008). An emerging stream of MC related research has recognized the importance of social influence processes in the context of self-designable products (Franke, Keinz, and Schreier 2008; Moreau and Herd 2010), and the development of community-based customization systems by firms highlights the need for research on socially enriched MC systems. For example, companies such as Porsche and Audi have developed community-based MC systems (so-called "color stylers") embedded within the online social network site Facebook, or as Lego and Threadless offer not only highly sophisticated toolkits for individual self-designs but also encourage consumers to post their designs within a company-led community and to share and revise designs with other users. Thus, the previously isolated context of MC systems is changing, and the integration of user communities is growing rapidly (Franke, Keinz, and Schreier 2008).

These developments not only offer new opportunities for sellers, but they also demand a new research perspective on consumer behavior in socially enriched MC systems. The present work takes an important step in this direction. It seeks to answer the following questions: (1) How do consumers balance their own preferences and community feedback when self-designing products? (2) How does community feedback affect consumers' post-decisional evaluation of self-designed products? (3) What are the implications of providing socially enriched MC systems for sellers?

We present evidence from a field study conducted in a large European car manufacturer's brand community and from three lab experiments. The findings show that consumers rely heavily on community feedback when designing their own products in socially enriched MC systems. In particular, receiving feedback on their initial self-design suppresses consumers' creativity in that they ultimately select self-designed products that are less unique, and this ultimately leads them to be less satisfied with their final self-designed product. However, despite this negative impact on consumer welfare, the results of Monte Carlo simulations that examine the implications of consumers' convergence towards more "average" (i.e., more common) self-designed products for the required assortment size suggest that community feedback may actually increase seller profitability.

2. Literature Review

Research on self-designable products and MC systems has increased significantly during the last decade (e.g., von Hippel and Katz 2002; Randall, Terwiesch, and Ulrich 2007), and the majority of past findings suggest that the success and market diffusion of self-designable products is due to increased opportunities for consumers to express their idiosyncratic preferences, which results in an increased preference fit of individually tailored products (e.g., Ghosh, Dutta, and Stremersch 2006). Prior research has also suggested that the opportunity for consumers to design their own products delivers a significant value increment through differentiation from other consumers (Franke and Schreier 2008). This increased consumer benefit from owning self-designed products is inherently related to Snyder and Fromkin's (1977, 1980) seminal work on individuals' need for uniqueness. According to uniqueness theory, people want to pursue and maintain moderate levels of distinction with regard to others (Fromkin 1970). Individuals strive to maintain the optimal balance between feeling either too similar or too different from others (Brewer 1991), and differentiation through consumption choices can serve the purpose of communicating one's desired personal identity to others (Berger and Heath 2007).

The notion that the creation of unique products is a key value driver of MC is consistent with Lynn's (1991) meta-analysis of scarcity effects in consumer research and his finding that owning a rare product generates value to a consumer (see also Thompson and Haytko 1997). This value increment of uniqueness is also empirically supported by prior findings in various domains, such as clothing, wine, art prints, and also food or soft drinks (for a review, see Ruvio 2008). Thus, the benefits to consumers from the use of MC systems to self-design products and to "adjust product features to their unique preferences" (Franke and Schreier 2010, p. 1022) are in line with prior research in both marketing and psychology.

However, in contrast to this preference for uniqueness, work on social influence suggests that individuals' thoughts and actions are often significantly affected by the (actual or anticipated) presence of other people (for a review, see Wood 2000). Thus, while consumers may have a desire to feel distinct from others, their attitudes, preferences, and behavior are not independent of the attitudes, preferences, and behavior of others in their social environment. For instance, Simonson and Nowlis (2000) found that consumers' pursuit of individuality and uniqueness is inherently constrained by the desire for social approval.

The initial evidence on the effectiveness of socially enriched MC systems is mixed. For example, Kramer, Spolter-Weisfeld, and Thakkar (2007) showed that consumers with an interdependent orientation are inclined to prefer products that reflect the aggregated preferences of other consumers, whereas those with an independent orientation tend to instead rely more on their own preferences. Furthermore, a series of studies by Franke, Keinz, and Schreier (2008) revealed that integrating user communities into self-design processes increased user satisfaction, purchase intention, and willingness to pay. However, Moreau and Herd's (2010) studies identified a potential drawback of social comparisons in self-design processes—their findings suggest that comparing one's own with other's self-designed products can reduce satisfaction. Thus, factors such as social comparison processes and anticipated feedback from other individuals may influence the evaluation of self-designed products.

This body of prior work leads to the conjecture that, to the extent that consumers' preferences are constructed in the course of making a product choice (e.g., Bettman, Luce, and Payne 1998), especially after interactions with other consumers, a basic premise of MC is challenged: although consumers might value the opportunity to self-design their products in order to express their individuality and uniqueness (Franke and Schreier 2008), they have to strike a balance between achieving an appropriate amount of uniqueness and not deviating excessively from what other consumers may deem adequate and socially acceptable.

In sum, past research on user-design and MC has emphasized the value expressiveness function of individually tailored products and the notion that self-designed products closely reflect consumers' idiosyncratic preferences (Syam, Ruan, and Hess 2005). However, as MC systems are shifting toward the integration of user communities, any attempt to understand consumer decision making in connection with such systems must consider how feedback from others affects consumers' product self-design decisions.

3. Development of Hypotheses

We conceptualize the consumer's product self-design processes in socially enriched MC systems as consisting of the following stages: (1) specifying an initial self-design, (2) receiving feedback on this initial design from other community members, and (3) choosing the final self-designed product. We propose that community feedback plays an important role in the product self-design process. In particular, receiving feedback on an initial self-design should invoke social comparison tendencies (Buunk and Gibbons 2007). Such feedback need not be an explicit evaluation of one's initial self-design by others—it may merely take the form of an alternative product design. The opportunity to observe similarities, and especially dissimilarities, should increase the propensity to conduct inter-individual comparisons and to evaluate one's initial self-design relative to someone else's proposed design (e.g., Moschis 1976).

We hypothesize that this type of community feedback causes consumers to deviate from their initial self-design and shift towards the alternative designs proposed by other individuals, resulting in an increase in the probability of choosing more easily justifiable compromise options (Simonson 1989). In particular, it has been shown that "thinking about others' choices appears to increase the share of the conventional, middle option" (Simonson and Nowlis 2000, p. 56) and choosing a less extreme middle option may decrease the likelihood of criticism from other consumers. Thus, we predict that this extremeness aversion leads to the assimilation of the initial self-design toward the community feedback, and that this effect is amplified for consumers who initially created more extreme self-designs.

H1a: Receiving community feedback relative to consumers' initial self-design results in assimilation towards the received community feedback when choosing the final self-designed product.

H1b: Deviations from more extreme initial self-designs are stronger than deviations from less extreme (i.e., intermediate) initial designs.

Moreover, past research has revealed that receiving feedback from a kind person results in increased conformity due to reciprocity effects (e.g., Rafaeli and Sutton 1991). In addition, it has been shown that the perceived competence of feedback providers tends to enhance the latter's influence on focal decision makers (e.g., Cialdini and Goldstein 2004). Thus, we predict that the extent of deviation from consumers' initial self-designs is higher when feedback providers are high in perceived competence and high in liking.

H1c: The higher the perceived competence of the feedback provider, the greater consumers' deviations from their initial self-design.

H1d: The higher the liking of the feedback provider, the greater consumers' deviations from their initial self-design.

The influence of community feedback on consumers' final self-design might also have implications for the variety of consumer self-designs. One possibility is that the interaction with others might boost the creativity of self-designed products since the exchange of ideas could identify designs previously not considered. However, decades of research in the area of creativity have consistently shown that individuals working separately generate more creative ideas than groups because "rather than exploring a diverse set of ideas participants might conform to the categories of ideas suggested by other group members" (Kohn and Smith 2010, p. 362; see Mullen, Johnson, and Salas

1991 for a review). Thus, social interactions tend to inhibit creative processes, and the fear of negative evaluations by others can prevent creative outcomes.

Although the definition and measurement of creativity depends on the specific context and level of analysis (see Hennessey and Amabile 2010), one widely accepted definition ties creativity to the novelty and value of the created output (Amabile 1983). We build on the body of prior work that has viewed creativity as an end result rather than a process (e.g., a particular way of approaching a problem) or an enduring personal characteristic (Hennessey and Amabile 2010) and adopt the common definition of creativity based on the novelty and uniqueness of a consumer's final self-design relative to the set of designs developed by other consumers (Torrance 1988). Accordingly, we operationalize the creativity of self-designed products in terms of the variety of selected product attributes across consumers, and we predict that the convergence toward the preferences of others in the presence of community feedback results in less variety in the attributes of self-designed products relative to consumers' initial self-designs (specified in the absence of community feedback).

H2: Community feedback reduces the variety of self-designed products across consumers.

To the extent that receiving feedback on one's initial self-design from others results in the hypothesized convergence towards products that are more common (i.e., less creative), this might also affect how satisfied consumers are with these products. Work by Moreau and Herd (2010) suggests that social comparisons can lead to less favorable evaluations of self-designed products, particularly when consumers fail to engage in mental processing or behaviors designed to protect their self-image. Moreover, research by Dahl and Moreau (2007) indicates that consumers perceive the lack of uniqueness of the outcome of a creative task as a significant drawback, and that this may diminish their satisfaction. In line with these findings, we predict that greater deviations from initial self-designs as a result of community feedback not only reflect stifled consumer creativity, but that they also render consumers less satisfied with their self-designed products.

H3a: The greater consumers' deviations from their initial self-designs as a result of community feedback, the lower their satisfaction with self-designed products.

The revision of a consumer's initial self-design in response to receiving community feedback on it may increase the uncertainty associated with his/her ultimate self-designed product. In turn, decision uncertainty can have a negative impact on consumer satisfaction (e.g., Heitmann, Lehmann, and Herrmann 2008). Thus, we hypothesize that the effect of the magnitude of the deviation from an initial self-design on how satisfied consumers are with their self-designed products is mediated by decision uncertainty.

> **H3b:** The negative impact of the magnitude of deviations from consumers' initial self-designs on satisfaction with the final product is mediated by decision uncertainty.

Moreover, the extent to which a consumer feels that his/her initial self-design must be revised upon receiving community feedback on it may also nourish the perception that the self-design process is a complex one. Prior work by Dellaert and Stremersch (2005) has revealed that the perceived complexity of the MC process is a key determinant of consumers' utility from self-designed products. In line with this, we hypothesize that the negative effect of the magnitude of deviations from initial self-designs on satisfaction with the ultimate product (H3a) is also mediated by how complex consumers perceive the self-design process to be.

> **H3c:** The negative impact of the magnitude of deviations from consumers' initial self-designs on satisfaction with the final product is mediated by the perceived complexity of the self-design process.

If consumers, as we predict, revise their initial self-design in response to community feedback, the nature of their self-designed products might be systematically influenced even if they merely anticipate receiving such feedback. Since individuals tend to seek approval from both known and unknown others (Baumeister and Leary 1995), and even shift their attitudes towards those held by anticipated audiences (Klimoski and Inks 1990), we predict that consumers' self-designed products are systematically influenced by the mere expectation of receiving community feedback on them. More specifically, in line with the prior finding that consumers who anticipate being evaluated by others tend to shift their choices towards more easily justifiable product attributes (Simonson and Nowlis 2000), we hypothesize that expecting to have one's product configuration evaluated, and commented on, by someone else reduces the tendency to choose uncommon product attributes.

H4a: The mere anticipation of community feedback on their self-design reduces consumers' choice of uncommon product attributes.

The tendency to create less ostentatious self-designs when expecting community feedback may be stronger for some consumers than others. In particular, consumers who are less knowledgeable in connection with the product domain may have a greater need for external information (e.g., Bettman and Park 1980). For instance, consumers with low domain knowledge may choose compromise options in order to avoid threatening judgments by others (Sheng, Parker, and Nakamoto 2005). Based on this, we hypothesize that anticipated community feedback has a stronger (negative) effect on the selection of uncommon product attributes among consumers who are less knowledgeable in the product category.

H4b: The negative effect of the anticipation of community feedback on the choice of uncommon product attributes is stronger for consumers with low domain knowledge.

Consumers differ in how susceptible they are to interpersonal influence (Bearden, Netemeyer, and Teel 1989) and prior research has shown that consumers groups who are sensitive to external influence are less likely to choose conspicuous products (Lynn and Harris 2006; Simonson and Nowlis 2000). Thus, we hypothesize that the negative effect of anticipated community feedback on the tendency to select uncommon product attributes (H4a) is stronger for individuals who are chronically more socially susceptible.

H4c: The negative effect of the anticipation of community feedback on the choice of uncommon product attributes is stronger for consumers with high social susceptibility.

Finally, extending hypothesis 2, we predict that not only actual feedback, but also anticipated feedback leads to a reduction in the variety of attributes of self-designed products across individuals.

H5: The mere anticipation of community feedback reduces the variety of self-designed products across consumers.

4. Field Study

4.1 Context and Data Collection

To test the first hypothesis regarding the assimilation of initial self-designs toward the received community feedback, the authors accompanied a large European car manufacturer during a pilot study to track inter-temporal self-design changes at the individual level as well as to track exchange processes between distinct individuals. The company developed a tracking tool that is able to store all events in a database consisting of the complete product information regarding model type, extras and vehicle equipment, engine version, car price, and so forth. Herein, customers can choose from 14 different attribute categories (e.g., light system, interior décor, safety systems, seats, chassis, etc.) with an average of 8 attributes per category (SD = 4.8). The process of vehicle self-design and exchange is as follows: customers and prospective customers design their personal car and are able to store the self-designed car in the manufacturers' online system. After customers designed their personal car they were able to sent their self-designed configuration to another person, and the car manufacturer's system tracked every exchange process. For example, consider that you are on the company's website in order to design your personal car. When you have finished the initial self-design you might be interested in what your friends think about the design and chosen extras. Thus, you pass your design in the community backend to your friend and invite her to comment on and/or redesign your initial choice. Your friend receives your invitation for sharing your initial design, and after she has modified your self-designed car according to her own preferences, you receive a message from her regarding her modifications. The car manufacturer's system tracked every event of this self-design history, and we gained access to a complete dataset of 149 designs by different individuals who created and exchanged their self-designed car between October 2010 and January 2011 as well as a control sample of 684 customers who self-designed their car but received no feedback from other users. Due to privacy reasons, we were able to analyze the respective self-designed cars but not the individual-level information (e.g., length of community membership, gender, age, etc.) or the exchanged text messages.

4.2 Dependent Variables

Since hypothesis 1 is related to the influence of community feedback on deviations from initial self-designs, we employed the following procedure: to measure the degree of deviation from an initial self-design, we applied a weighted Euclidean distance metric according to Shocker and Srinivasan (1974) and standard preference modeling procedures. The underlying rationale is that one should capture (1) positive and negative attribute deviations from the initial design (e.g., choosing an attribute of higher or lower value compared to the initial design) and (2) the inter-individual heterogeneity of the attribute importance, for example, low deviations within highly important attributes or vice versa. Thus, our algorithm estimated the Euclidean distance between the initial and final self-design first and then weighted this difference with an individual weighting parameter that corresponded to the participant's importance of each attribute category. All individual weights sum up to one. We will call this measure in the following the aggregate deviation index (ADI):

$$\mathrm{ADI}_i = \sum_{c}^{C} \sqrt{(\tau_{ic}(t_1) - \tau_{ic}(t_2))^2} \times \omega_{ic} \tag{1}$$

with the choice of attribute τ by individual i in category c, at time t_1 and t_2 and the individual category importance ω. To capture individual differences within attribute categories, the importance of an attribute category is reflected by the amount of money consumers spent on it, reflecting the utility increase subject to individual budget constraints (e.g., Hauser and Urban 1986). Thus, we model the weighting parameter ω based on the differences of consumers' budget allocation for the respective attribute and the absolute maximum within these attributes. Thus, the weighting parameter reflects the percentage of attribute investments, and is modeled by:

$$\omega_{ic} = \frac{\sqrt{(\text{Price } \tau_{ic}(t_1) - \text{Price } \tau_{ic}(t_2))^2}}{\max\,(\text{Price } \tau_c)} \tag{2}$$

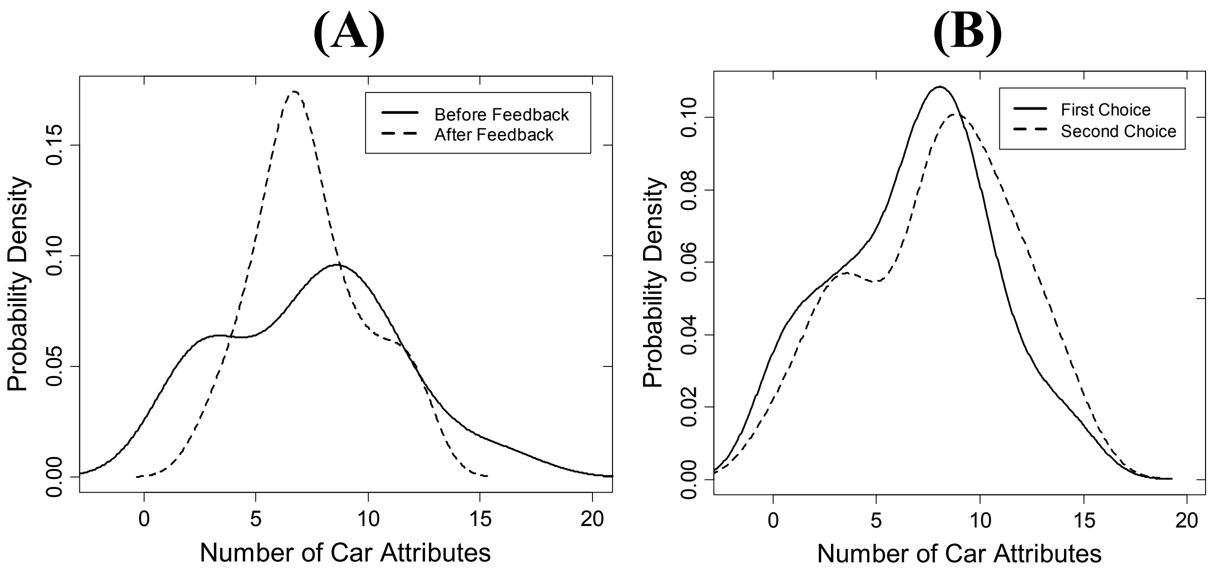
4.3 Results

To test hypothesis 1a, we applied linear models to predict customers' final self-design based on the received community feedback. In particular, we predicted that receiving community feedback leads to the assimilation of initial self-designs toward the given community feedback. We built fourteen simple one-predictor linear models and regressed customers final self-design attribute choice on the received community feedback. We found empirical support for our prediction, as all predictors were positive significant and explained final choices reasonably well ($M_{Beta} = .02$, $M_{t\_value} = 9.982$, $M_R{}^2 = .42$). Furthermore, and as expected, we also found that customers with more extreme initial choices, reflected by option choices in the upper quartile of the categories, deviated more strongly than customers with more intermediate choices ($M_{ADI\_Extreme\_Choices} = .0065$, $M_{ADI\_Intermediate\_Choices} = .0015$, $t(2084) = 6.484$, $p < .05$) and received more distant feedback compared to customers with more intermediate initial choices ($M_{ADI\_Extreme\_Choices} = .107$, $M_{ADI\_Intermediate\_Choices} = .033$, $t(2084) = 6.095$, $p < .05$). To rule out possible confounded influences that may have yield qualitative differences in influence on the category level, like differences between hedonic vs. utilitarian features (e.g., exterior packages or interior decor elements vs. park assistance or car seats) or differences regarding community feedback to up- or downgrade, we conducted additional tests: first, we found that up- and downgrades occurred in equal frequency ($\chi^2(2, N = 149) = 14.588$, $M_{p\text{-}value} >.66$). Second, two coders assigned all categories to either hedonic or utilitarian features (inter-rater reliability: $\kappa = .92$), and we found that although hedonic features yielded a higher amount of explained variance and slightly steeper regression slope ($M_{Beta\_Hedonic} = .028$, $M_R{}^2 = .47$; $M_{Beta\_Utilitarian} = .019$, $M_R{}^2{}_{\_Utilitarian} = .38$), these differences were not statistically significant ($t_{Betas}(14) = -0.803$, $p > .43$; $t_R{}^2(14) = -0.802$, $p > .43$). Thus, hypothesis 1a and 1b are finally supported.

To test hypothesis 2, if the attribute variability of final self-designs is lower compared to initial self-designs, we applied equality of variance tests on the category data. Herein, attribute variability is operationalized by the relative frequencies of all chosen attributes within an attribute category of all customers initial designs compared to final designs. To test our predictions, we applied Mood's Test for differences in scale parameters (Mood 1954), since the test statistic is appropriate for testing directional hypotheses concerning scale variability of attributes, as the nonparametric analog to the two-sample F-test for equality of variances (Gibbons and Chakraborti 2003). As Figure 1 shows for consumers whose final self-design was not identical to their initial design, although the location parameter of the distribution of car extras is identical, the distributional variability is significantly lower compared to the initial distribution (Mood's Scale Test: $z = 1.794$, $p < .05$). For example, the car manufacturer's portfolio of different vehicle seats offers about 10 different versions (a basic model, one with electronic adjustment, another with memory function, and several others with additional functions). As expected, the variability of chosen car seats was significantly lower after customers received community feedback compared to the initial distribution of seat choices (Mood's Scale Test: $z = 1.692$, $p < .05$).

To rule out the possibility that customers who are not part of the community and weren't able to exchange their self-designs may also deviate from their initial self-design, we conducted additional tests with a control sample of customers. In particular, we analyzed the data of 684 customers who also self-designed their car but have not exchanged their design within the brand community. As expected, we found that the initial self-design of the car during the first self-design process already matched customers preference reasonably well as we found no statistical difference in attribute variability for customers chosen car attributes in the first self-design compared to the second self-design (Mood's Scale Test: $z = 0.790$, $p > .78$) as well as a significantly lower deviation from their initial self-design compared to the community sample ($M_{ADI\_Control\_Sample} = .014$, $M_{ADI\_Community\_Sample} = .032$, $t(831) = 4.942$, $p < .05$).

Figure 1: The Reducing Effect of External Feedback on the Variability of Chosen Attributes



Note—(A) community sample with exchange of car designs and (B) control sample of customers without exchange of individual designs and receiving no feedback.

Thus, in the case of isolated self-design procedures, MC systems allow customers to express their individual preferences reasonably well and only minor changes during the self-design process occur. However, we have shown that results significantly change within socially enriched MC systems.

4.4 Discussion

The results of the field study showed that the received community feedback were strong predictors of customers' final design choices and was of equal strength for hedonic and utilitarian attributes as well as the valence of the feedback (up- vs. downgrades). In addition, we found empirical evidence that the variability of chosen self-designs after social interactions was significantly lower and that customers chose significantly less extreme designs and converged toward the intermediate range of designs. The use of a control sample with customers who have not exchanged their car design, revealed additional evidence that customers conduct only minor modifications of their initial self-design, suggesting that standard MC systems allow consumers to express their individual preferences reasonably well.

However, the robustness and boundary conditions of these initial effects remain unclear. For example, since we were not able to control for dependencies between community feedback and consumers' initial self-design (e.g., larger deviations for more extreme initial self-designs), it will be important to manipulate the magnitude of distant community feedback independent of individuals' initial self-design. Furthermore, it will be interesting to test how these effects are moderated by characteristics of the feedback provider, such as competence or liking. In addition, although one can predict final choices based on given feedback reasonably well, it is less clear how post-decisional perceptions are affected if final choices are not only based on one's own preferences. Furthermore, it will be interesting to see if self-design decisions might already be altered by the mere anticipation of an external community feedback and how these subtle influences might already shape consumers' preferences. We examined these questions in a series of lab experiments.

5. Lab Experiments: Overview and General Method

We conducted a number of lab experiments to test the robustness of these previous results (e.g., reduced creativity in self-designs and strong deviations from initial self-designs), important post-decisional effects such as satisfaction with the self-designed product or feelings of uncertainty, relevant boundary conditions (e.g., dependencies of consumer characteristics such as domain expertise or social susceptibility) as well as theoretical and practical extensions (e.g., the mere influence of anticipated evaluations on user self-designs).

To run our lab experiments, we developed an online community platform as well as a consumer product customizer. Programming our own community platform enabled us to manipulate the nature of the feedback and the specific characteristics of the feedback provider in every detail such as information regarding the expertise level. We built a product customizer in the area of self-designable earrings and chose the jewelry domain as our experimental product category due to its high social perceptibility (Amaldoss and Jain 2005). Although the categories of cars and jewelry may differ in terms of inherent decision uncertainty, absolute price range, and so forth, our main interest is to test the generalization for another product category within the domain of socially visible goods. As a general procedure, we invited participants to join our manipulated community platform and log themselves in to the member area. In all experiments, this area introduced participants to the general procedure of the study and presented our developed MC system to tailor an individual pair of earrings, consisting of 188 jewelry items overall in four categories (ear-hook and small, medium, and large jewelry items). Figure 2 provides a sample screenshot of the experimental interface.

Figure 2: Experimental Framing of the "Jewelry Community" and Product Customizer

A pretest was conducted to (1) develop the experimental jewelry stimuli that are likely to be chosen in a real market setting and (2) determine the order of presentation for further analyses and as a basis for our experimental manipulations (e.g., to present the attributes based on their value of novelty or conspicuousness). During the pretest, we asked participants to choose one jewelry item within the following categories: an ear-hook, a small jewelry item, an intermediate item, and a large jewelry item. At the time of our study, consumers perceived the composition of four elements as one of the market-wide dominant earring designs (www.rockberries.com), which also offered enough possibilities for experimental variations. Since we could not control for physiological restrictions at the individual level, we manipulated all categories except for the first one (ear-hook vs. ear-clip). We explicitly derived the order of presentation of our stimulus material from existing design research (e.g., Orth and Malkewitz 2008). We pretested our stimuli with 32 subjects within two distinct tasks. As part of the first task, participants described the presented jewelry items within an open-ended question format. In the second task, participants looked at all jewelry items again and rated every gem according to dimensions considered central for aesthetic evaluations within the design research literature (Orth and Malkewitz 2008). In particular, participants evaluated each of the jewelry items based on a semantic differential with 10 bi-polar items on seven-point scales ("plain vs. angular", "smooth vs. textured", "simple vs. abstract", "fine vs. coarse-grained", "even vs. uneven", "small vs. large", "common vs. unique", "traditional vs. novel", "monotonous vs. interesting", "harmonic vs. discordant"). This procedure allowed us, in addition to the subjective and exploratory evaluation of the first procedure, to evaluate textual, form-specific, and other relevant differences between the items.

We performed an exploratory factor analysis (EFA) on every jewelry item for all evaluated dimensions. The EFA results showed that a two-factor solution could reasonably well aggregate all jewelry items: the first factor is based on the "common vs. unique", "traditional vs. novel", "monotonous vs. interesting" scales and can be summarized as the "perceived novelty" of the jewelry items ($M_{Explained\_Variance} = 81\%$, 95%-CI = [77%; 85%]; scale reliability: $M_{\alpha} = .88$). All other scales ("plain vs. angular", "smooth vs. textured", "fine vs. coarse-grained", "even vs. uneven", "small vs. large", "harmonic vs. discordant") explained an average amount of 68% of variance (95%-CI = [64%; 71%]) and can be summarized as the "visual conspicuousness" of the jewelry item. We also confirmed the scale's reliability ($M_{\alpha} = .83$). The simple vs. abstract scale was finally excluded due to high cross loadings on both latent dimensions ($M_{perceived\_novelty} = .67$; $M_{visual\_conspicuousness} = .78$). The parsimonious two-factor solution also confirms former design research findings of a general holistic processing of visual stimuli (Bloch 1995). In addition, we carefully assessed the possibility of potentially missing dimensions with a content analysis of participants' subjective reasons for the ranking procedure. Two independent coders assessed the respective dimensions and found that all answers could be grouped within the existing dimensions reasonably well (inter-rater reliability: $\kappa = .90$).

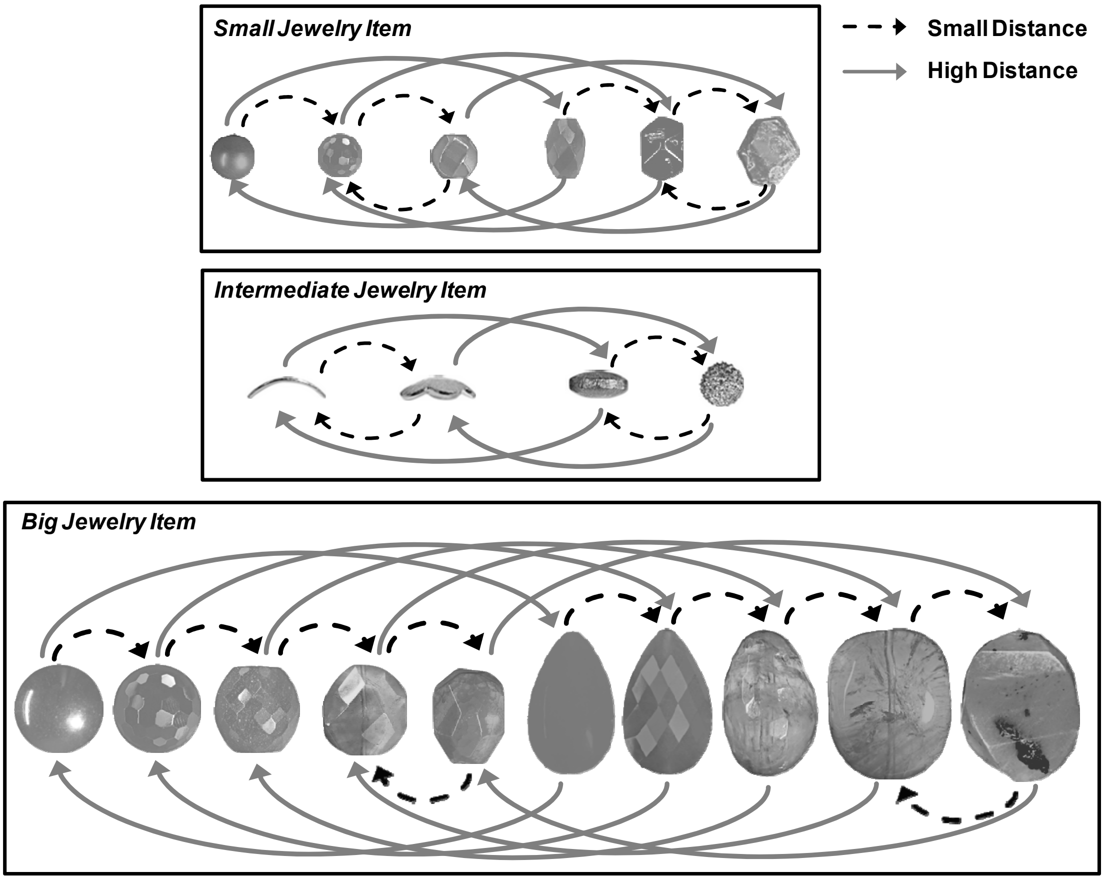
The final order of presentation (see Figure 3) was based on participants' aggregated ranking order, which was equal to the means of both latent dimensions. Thus, all jewelry items increased in novelty (first factor) and visual conspicuousness (second factor) from left to right.

5.1 Lab Experiment 1a: Feedback-Giver Characteristics and Deviation of Self-Designs

5.1.1 Experimental Design and Procedure

In this first experiment, we test the influence of feedback-giver characteristics on deviations in consumers self-designs. At the beginning of the experiment, participants were invited to the community platform and were given the opportunity to design their personal earrings based on the choice of one jewelry item in each of the four previously described jewelry categories. After all participants designed their personal earring, they were led to believe that their self-designed earring would be passed to another community member to get a personal feedback and that the participants would be re-invited after a time lag of 48 hours in order to apply any redesign if needed. When participants logged in again, they received a (manipulated) feedback message, and they then had the opportunity to change their initial self-design if they wished. Three aspects of the feedback were manipulated: (1) the degree of competence of the feedback provider, (2) the participant's liking of the feedback provider, and (3) the distance of the community feedback from the participant's initial self-design. To manipulate competence, the feedback provider identified herself either as a professional jewelry designer or as an employee of a butcher shop. The manipulation of liking was implemented as follows. In the high-liking condition, the feedback provider was of similar age (2 years older) as the participant, had a first name with the same first letter as the participant's (based on the finding that shared initial letters in first names lead to positive affect towards another person; see Wentura, Kulfanek, and Greve 2005), and used favorable emoticons (smileys) in her feedback. By contrast, in the low-liking condition, the feedback provider was 15 years older, did not provide her name, and did not use any emoticons in her feedback. Finally, the extent of preference distance of the feedback was manipulated such that the presented community feedback was either close (low distance condition) or substantially different to the participant's initial self-design (high distance condition). Every jewelry item was given a unique index value and the manipulation of both conditions was conducted by applying an algorithm that generated the community feedback automatically by shifting the initial design by either 1 (low distance) or a larger number of jewelry items (dependent on the respective jewelry category; see Figure 3 in detail). For example, if an individual chose item No. 2 of 10 possible items of the big jewelry items, she received a feedback of jewelry item No. 3 in the small distance condition and jewelry item No. 7 in the high distance condition.

Figure 3: Graphical Illustration of Experimental "Preference Distance" Manipulation



Note—Illustration shows the two conditions of the experimental factor "preference distance". For example, customers in the small distance condition who chose jewelry item No. 1 will receive feedback for jewelry item No. 2 and participants in the high distance condition feedback for jewelry item No. 4, as the first jewelry item in the next subcategory.

Thus, we applied a 2 (high vs. low competence) × 2 (high vs. low liking) × 2 (high vs. low preference distance of community feedback) between subjects design to test the influence of external community feedback on self-design deviations. A total of 1092 female members of an online consumer panel participated in the experiment ($M_{Age} = 35$, SD = 10.1).f

5.1.2 Dependent Variable

To measure the influence of community feedback on deviations in consumers' self-designs, we applied the same weighted Euclidean distance measure as in our field study (aggregate deviation index (ADI), see equation (1)). The weighting parameter ω (see equation (2)) was measured explicitly based on a constant-sum rating of each category importance by assigning a number out of 100 to one category and 100 minus the previous number on the remaining categories. Again, all weights sum up to one.

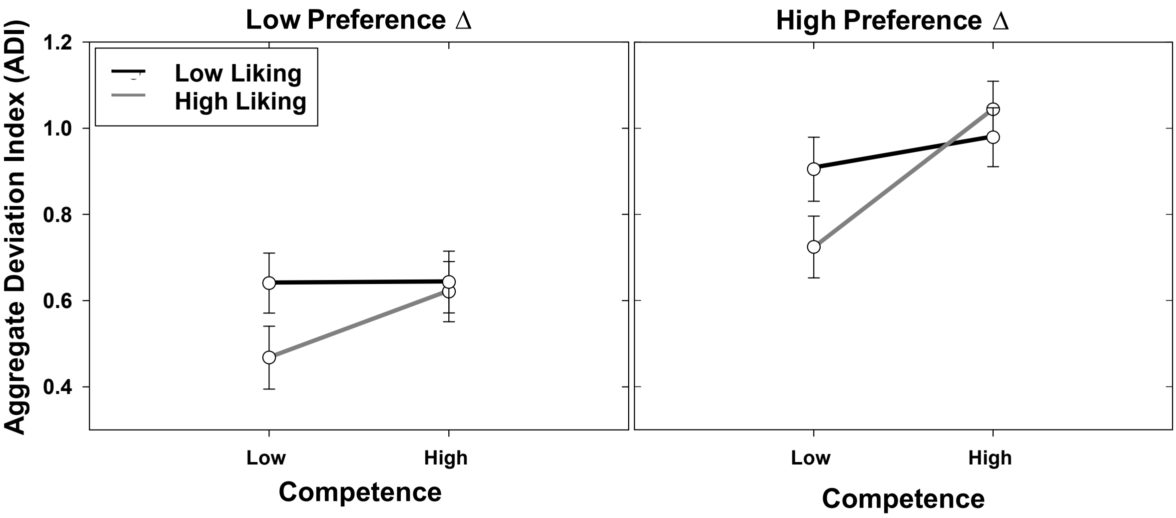
5.1.3 Manipulation Checks

As expected, participants perceived the feedback provider in the high competence condition as more competent ($M_{HighCompetence} = .32$ vs. $M_{LowCompetence} = -.35$, $t(1081) = 11.79$, $p < .01$) ("I perceived the feedback giver as … (1) competent, (2) professional in her advice, (3) a person who knows very well what she is talking about"), the high liking condition as more friendly and sympathetic ($M_{HighLiking} = .18$ vs. $M_{LowLiking} = -.19$, $t(1081) = 6.08$, $p < .01$) ("I perceived the feedback giver as … (1) friendly, (2) sympathetic, (3) offish (reverse coded)), and the high preference distance condition as significantly different from their initial design ($M_{HighPreference\Delta} = .10$ vs. $M_{LowPreference\Delta} = -.10$, $t(1081) = 3.29$, $p < .01$) ("The feedback I received was (1) identical, (2) slightly different, (3) highly different compared to my previous self-design"). Thus, the effectiveness of our experimental manipulations was confirmed.

5.1.4 Results

To test our hypotheses, we conducted a three-way ANOVA with the ADI metric as the dependent variable. First, the three-way interaction was not significant ($F(1,1082) = .23$, $p > .63$); hence, we can focus on the lower-order effects. Herein, the interaction between competence and liking was found to be significant ($F(1,1082) = 3.95$, $p < .05$). Follow-up contrasts showed that the liking effect varied significantly between the levels of low competence in the way that highly sympathetic feedback reduced its effect on self-design deviations ($M_{LowLiking,LowCompetence} = .77$ vs. $M_{HighLiking,LowCompetence} = .60$, $t(514) = 1.95$, $p = .05$). Surprisingly, we found that less sympathetic feedback in the low competence condition led to strong deviations in contrast to highly sympathetic feedback messages. A discussion based on possible authority effects follows below. Regarding the proposed main effects, we found the predicted and strongest main effect of the preference distance of community feedback on final self-designs: changing the community feedback from low to high distance yielded the strongest main effect ($M_{LowPreference\Delta} = .59$ vs. $M_{HighPreference\Delta} = .91$, $F(1,1082) = 41.17$, $p < .01$). Thus, the results support Hypothesis 1a again and replicate the findings of the field study. Remember that we did not present participants any reason why they should change their choice—just setting the community feedback from low to high distance revealed such strong effects on deviations in consumers' self-designs. We can also conclude a positive and significant main effect for highly competent feedback on the degree of final design deviations ($M_{LowCompetence} = .68$ vs. $M_{HighCompetence} = .82$, $F(1,1082) = 7.62$, $p < .01$). While the main effect for the liking condition is only close to marginal significance ($M_{Low\ Liking} = .79$ vs. $M_{High\ Liking} = .71$, $F(1,1082) = 2.42$, $p = .12$), the direction is again contrary to what we expected and in line with the previous interaction effect: the more sympathetic the person giving feedback, the less deviation in final self-designs.

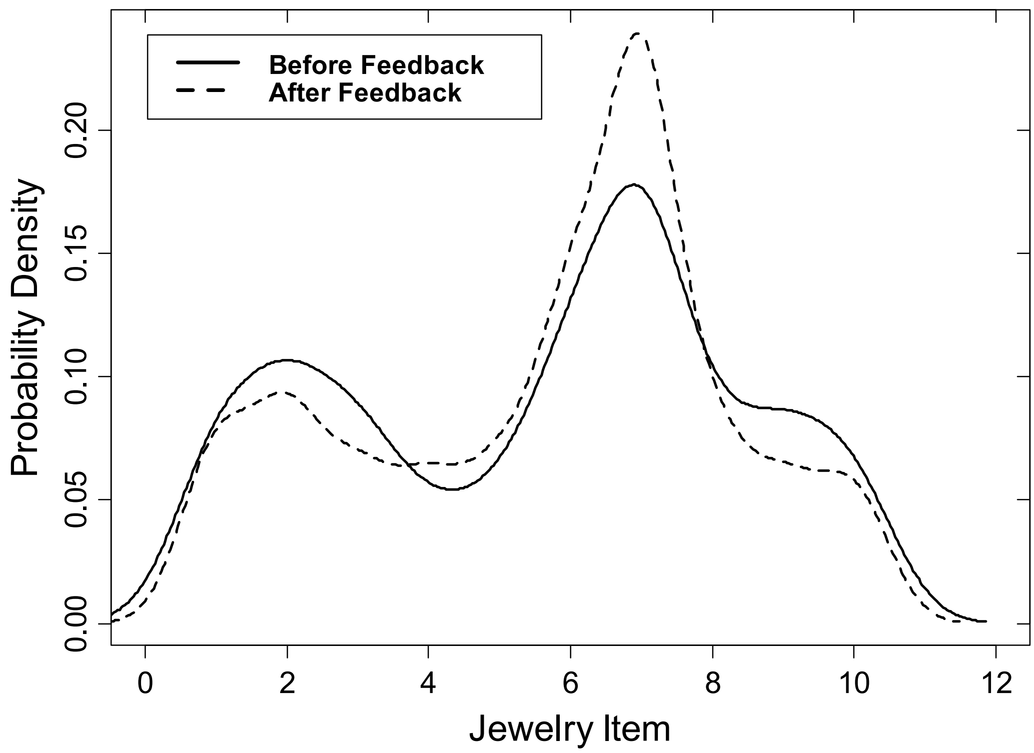
Figure 4: Effect of Competence, Liking, and Preference Distance on ADI



As in the field study, we also tested the hypothesized reduction in creative self-designs after receiving community feedback, reflected by the variability of novel attributes. As predicted, and in replication of the field study, we found that consumers' attribute variability was significantly reduced after receiving community feedback (Mood's scale test (small item): $z = 3.148$, $p < .05$; Mood's scale test (big item): $z = 4.020$,

$p < .05$). As Figure 5 shows, we find the same pattern of shifting distributions in that participants converged from the more extreme designs toward the mid-range of jewelry items.

Figure 5: The Reduction of Consumers' Attribute Variability in the Jewelry Study



To rule out the possibility that consumers at the more extreme ends may only shift toward the opposite extreme and consumers in the intermediate range shift slightly toward the middle, we tested for differences in participants' ADI. As expected, consumers who chose extreme initial self-designs deviated significantly stronger compared to consumers in the intermediate range ($M_{ADI\_IntermediateRange} = 59$, $M_{ADI\_ExtremeEnds} = 90$, $t(1090) = -6.155$, $p < .05$).

5.1.5 Discussion

The most important and replicated finding is that the shift of external community feedback reveals strong effects on self-design deviations without presenting any reasons from the decision-makers' point of view and that we found the same pattern of reduced creativity in self-designs after receiving external feedback as in our field study. Furthermore, although we confirmed the direction of the distance of the community feedback and competence of the feedback provider, the effect of a highly sympathetic feedback was not as expected. We suspect that the increased deviation in the low-liking condition is due to impressions of authority: while friendly feedback does not exert any inherent pressure to conform and opposing them may be relatively costless, a rather unfriendly feedback may reveal, despite threatening an individual's self-worth, an implicit authoritarian effect to conform. Future studies may explicitly test this underlying hypothesis of authority effects in anonymous community interactions.

While lab experiment 1a demonstrated the general effect of influencing individual self-designs, we will now carefully analyze potential drawbacks of these influence processes.

5.2 Lab Experiment 1b: Self-Design Deviations and Post-Decisional Effects

5.2.1 Design and Procedure

In our introductory field study, we were not able to analyze customers' satisfaction and other respective outcome dimensions of individuals' initial self-design. In particular, based on the data of the previously reported lab experiment, we will now analyze if, and how, increasing deviations affect post-decisional dimensions of consumers, such as satisfaction, choice uncertainty, and perceived complexity of the self-design process.

5.2.2 Dependent Variables

We measured the (1) general satisfaction with the self-designed product (assessed according to Homburg, Koschate, and Hoyer 2005), condensed by a single factor that accounted for 79% of explained variance ($\alpha = .91$) and confirmed by a subsequent confirmatory factor analysis (CFA) (CFI = .98; AVE = .73); (2) the subjective uncertainty of having made the right decision (measured with reference to Argo, Dahl, and Manchanda (2005) with 90% of explained variance, high reliability ($\alpha = .94$) and acceptable CFA results (CFI = 1.00; AVE = .85)); and (3) the perceived complexity of the self-design process (according to Dellaert and Stremersch (2005) as well as Arnold and Reynolds (2003) with 62% of explained variance and moderate scale reliability and CFA results ($\alpha = .69$ and AVE = .48)).

5.2.3 Results

To test the effect of deviations on consumers perceived product satisfaction through the influence of decision uncertainty and perceived process complexity, we specified a multiple mediation model (Preacher and Hayes 2008). We found that consumers' systematic deviations had negative effects on all relevant post-decisional dimensions. As expected, high deviations from initial self-designs revealed a negative influence on consumers' satisfaction with the final self-designed product ($Beta_{ADI} = -.19$, $t(1086) = 5.372$, $p < .05$). Furthermore, high deviations of consumers' initial self-designs led to an increase in decision uncertainty ($Beta_{ADI} = .173$, $t(1086) = -4.867$, $p < .05$) as well as perceived process complexity ($Beta_{ADI} = .071$, $t(1086) = -1.984$, $p < .05$) and both mediators were significantly related to consumers perceived product satisfaction ($Beta_{ProcessComplexity} = -.14$, $t(1086) = 6.680$, $p < .05$; $Beta_{DecisionUncertainty} = -.75$, $t(1086) = -35.756$, $p < .05$). Herein, when controlling for the proposed meditational effect of decision uncertainty and process complexity, the negative effect of self-design deviations was still negative and significant but lower in absolute magnitude ($Beta_{ADI \mid Complexity,Uncertainty} = -.05$, $t(1086) = -2.662$, $p < .05$). Overall, the total effect of the meditation model was significant ($z = 4.633$, $p < .05$), and contrasts between both mediators revealed that the meditational effect of decision uncertainty was significantly stronger than the perceived complexity of the decision process (contrast decision uncertainty vs. process complexity = .119, $z = 4.931$, $p < .05$).

5.2.4 Discussion

These findings are important as they show that although consumers are systematically influenced by external community feedback (lab experiment 1a and field study), one has to consider the potential downside of influencing consumers' preferences carefully. It is very likely that others' opinions and feedback challenge consumers' internal consistency as balancing feedback and internal preferences is mentally exhausting and stressful. The meditational analysis revealed additional process evidence that this negative influence of self-design deviations on satisfaction with self-designed products is mediated by the perceived complexity of the self-design process as well as consumers' uncertainty about their final self-design.

Since we have focused so far on the core decisional as well as post-decisional effects of receiving explicit feedback, it will be interesting to see if consumers may choose differently even if they merely anticipate receiving community feedback. Thus, we will now test the influence of anticipated community feedback in the pre-decisional phase and the moderating role of consumer characteristics such as domain knowledge and social susceptibility.

5.3 Lab Experiment 2: Anticipated Feedback and the Choice of Uncommon Attributes

5.3.1 Experimental Design and Procedure

To examine whether and under what conditions anticipated community feedback, without explicitly knowing their preferences, affects individual self-designs (Hypothesis 4), we experimentally manipulated the timing of information that an evaluation will take place. We randomly assigned participants to the group that was informed before self-designing the product (pre-design condition) or to the group that was informed after the self-design had already been done (post-design condition). We told participants in the pre-design condition "your design will be directly forwarded to one of our community members after you completed the design process." By contrast, those in the post-design condition were not informed about the feedback until they had completed their initial self-design. To maximize the realism of our manipulation, participants were asked to answer questions about their favorite color, fashion preferences as well as eye and hair color that would be forwarded to another community member as well.

We recruited 327 female participants from an online consumer panel ($M_{Age} = 35$, $SD = 9.3$). Participants visited the community web page and logged in to start the experiment.

5.3.2 Dependent Variable

To assess consumer preferences for ostentatious attributes, we derived a simple measure that is closely related to the results of our pre-study. Remember that the order of presentation of all attributes is based on increasing values in visual conspicuousness and perceived novelty. To assess the extent of uncommon choices, our algorithm estimated the difference between the chosen attribute value and the smallest possible attribute value within the category and computed the ratio of this difference according to the maximum number of attributes within the category in order to normalize the index to a minimum of zero and a maximum of one. The larger the final index value, the stronger participants' tendency to choose more uncommon attributes. Thus, we define this final measure as the uncommon attribute index (UAI), which is conceptually related to standard dispersion measures for classified or grouped data (e.g., Watsham and Parramore 1997). More formally, we computed the UAI as follows:

$$UAI_i = \sum_{c}^{C} \frac{\tau_{ic} - \underline{\ell}_c}{\overline{\ell}_c} \tag{3}$$

with the choice of attribute τ by individual i in category c, the minimum $\underline{\ell}$ in c, and the maximum number of attributes $\overline{\ell}$ of each category c.

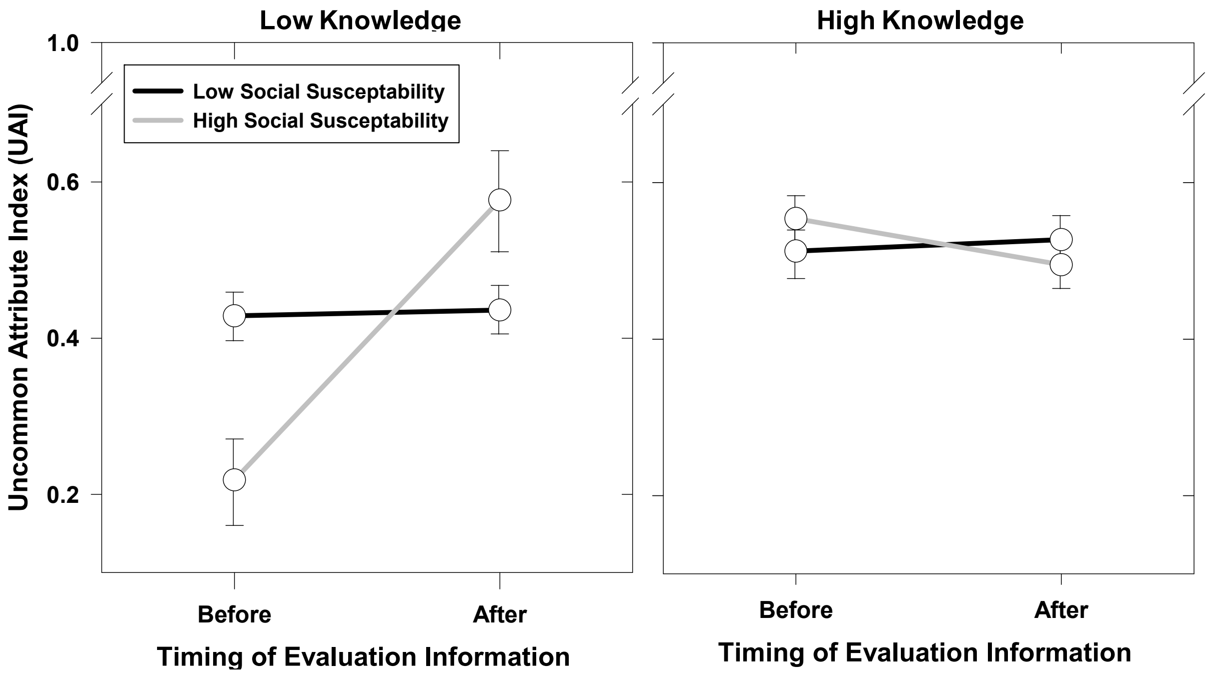
5.3.3 Moderating Variables

To control for moderating effects of individual conformity and domain knowledge (Hypothesis 4c,d), we measured participants' degree of susceptibility to peer influence with Bearden, Netemeyer, and Teel's (1989) scale (84% explained variance of latent variable and confirmed reliability ($\alpha = .95$)) and individuals' subjective domain knowledge according to Flynn and Goldsmith (1999) (87% explained variance and high scale reliability ($\alpha = .93$)). As the resulting factors are centered with zero mean and in order to ease interpretation of the results, we conducted a median split for the population of either low vs. high social susceptibility and low. vs. high knowledge; thus, we finally have a 2 (timing of evaluation information: before vs. after the self-design) × 2 (degree of susceptibility: high vs. low) × 2 (degree of subjective domain knowledge: high vs. low) between subjects design. All following results remain unchanged for the continuous version of individuals' conformity as well as domain knowledge.

5.3.4 Results

To examine whether anticipated community feedback affects subsequent self-designs, we tested Hypotheses 4 by conducting a three-way ANOVA. To prevent ambiguous interpretation of lower-order effects, we assess the three-way interaction first. In particular, the three-way interaction of timing of evaluation × susceptibility × knowledge was significant ($F(1,326) = 10.481$, $p < .01$). To examine the statistical differences within the respective factor levels, we performed follow-up analyses to detect those differences. As predicted, the follow-up contrasts showed that the systematic variation of uncommon attribute choices was dependent on participants' level of social susceptibility and was significant for subjects with below average domain knowledge (see Figure 6; $M_{PreDesign \mid LowKnowledge,HighSusceptibility} = .22$ vs. $M_{PostDesign \mid LowKnowledge,HighSusceptibility} = .58$, $t(30) = 4.673$, $p < .01$).

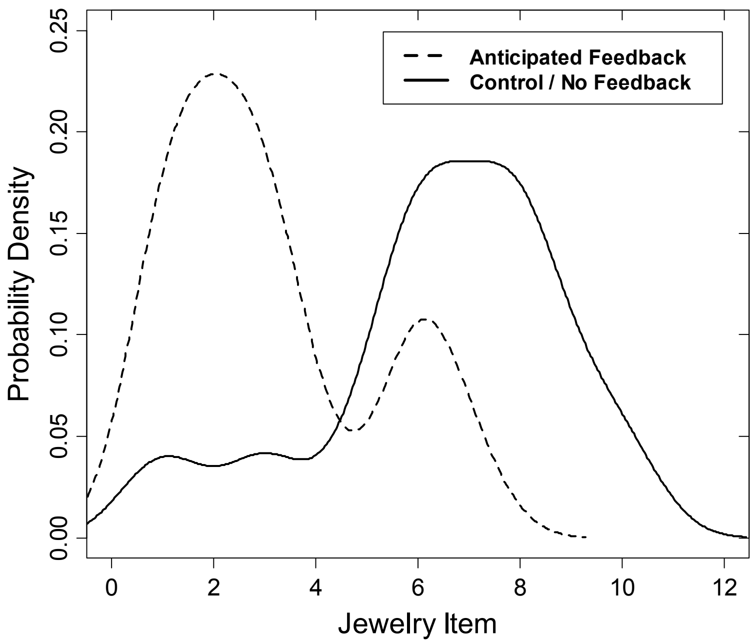
Figure 6: Anticipated Feedback and the Decreasing Choice of Uncommon Attributes



Furthermore, and as predicted, our results also revealed a significant main effect for the timing of evaluation: participants within the pre-design condition chose significantly fewer uncommon attributes than participants in the post-design condition ($M_{PreDesign} = .43$ vs. $M_{PostDesign} = .51$, $F(1,326) = 5.99$, $p < .05$). Thus, the results support Hypotheses 4a, 4c, and 4d. Although we also found a significant main effect for participants' knowledge ($M_{LowKnowledge} = .42$ vs. $M_{HighKnowledge} = .52$, $F(1,326) = 10.67$, $p < .01$) and additional two-way interactions which were in line with our general predictions, all effects must be evaluated with respect to the previous disordinal three-way interaction (in particular, timing of evaluation × susceptibility: $F(1,326) = 4.47$, $p < .05$) with follow-up contrasts indicating that highly susceptible participants chose fewer uncommon attributes in the pre-design condition and the same effect for low knowledge participants in the pre-design condition ($F(1,326) = 9.785$, $p < .01$).

Again, we also tested if consumers' attribute variability may decrease if participants anticipate community feedback (Hypothesis 4b). As predicted, and consistent with hypotheses 4b, we found that the creativity of conducted self-designs, reflected by the variability of novel attributes, is significantly reduced if consumers expect to get feedback from other community members in the case of the small jewelry item and close to marginal significance in the case of the big jewelry item (Mood's Scale Test (Small Item): $z = 2.812$, $p < .05$; Mood's Scale Test (Big Item): $z = 1.178$, $p < .12$). In essence, not only the number of creative self-designs was systematically reduced, but also the choice of uncommon attributes ($M_{UAI\_IntermediateRange} = .57$, $M_{UAI\_ExtremeEnds} = .22$, $t(28) = 4.472$, $p < .05$). Thus, and as Figure 7 shows, consumers tend to avoid more extreme self-designs in contrast to a control group who did not expected any community feedback before designing their personal product.

Figure 7: Anticipated Feedback reduced Variability and Preference for Uncommon Attribute



5.3.5 Discussion

The results of lab experiment 2 show that the mere anticipation of receiving community feedback has a strong effect on consumers' created self-designs. This effect is independent of any prior knowledge of others' preferences. As the follow-up contrasts of the three-way interaction showed, the shift of consumer preferences toward less ostentatious self-designs is strongest for consumers with high need for social approval and low domain knowledge. Again, we also replicated the reduced attribute variability finding of all previous studies in the context of anticipated community feedback.

5.4 Lab Experiment 3: Self-Design Deviations without Community Feedback

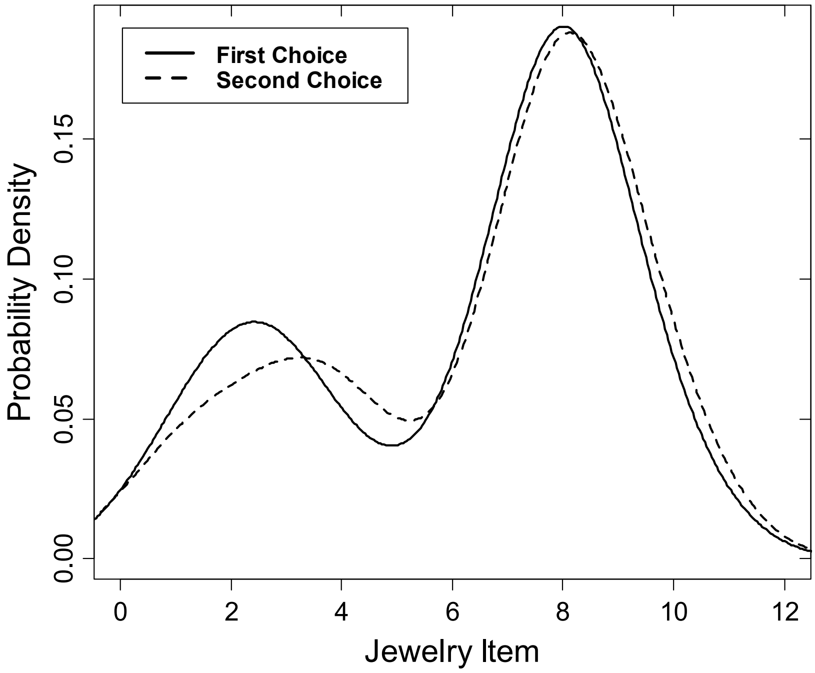
5.4.1 Design and Procedure

Although we found the same pattern of decreasing creativity of self-designs as in all previous studies, it may seem reasonable to hypothesize that differences in this variability may also occur without community feedback. Access to new information, changed preferences over time, or preference inconsistent choices in the first phase may seem rationale arguments from a consumer's point of view. In order to test the robustness of this previous effect, we conducted a final study to test for this possibility. The procedure was as follows: participants self-designed their personal earring and were automatically re-invited to our MC system after 48 hours to change their initial self-design if needed. Participants received no information about any community feedback and were simply given the opportunity to redesign their self-designed product. For this final study, we recruited 48 female participants from an online consumer panel (M_{Age} = 34.5, SD = 10.4).

5.4.2 Results

When participants received no feedback on their self-designed product, we found no differences in attribute variability over time (Mood's Scale Test (Small Item): $z = .1083$, $p > .45$; Mood's Scale Test (Big Item): $z = -3358$, $p > .63$), thus preferences remained fairly constant and we found no significant deviations between the initial and final self-designs.

Figure 8: Low Attribute Variability for Control Group With No Community Feedback



5.4.3 Discussion

This final study ruled out the possible alternative explanation that, even in the absence of any (experienced or anticipated) community feedback, consumers might tend to revise their initial self-design when given the opportunity to do so. However, we found that, although consumers made small changes to their initial self-designed product, the variability of self-designs remained constant. In turn, we may conclude that modern MC systems are means to express individual preferences reasonably well and consumers can converge closely to their optimal self-design. Thus, this final result also fortifies all our previously discussed results as we found that individual decision behavior changes considerably when social interactions (and even anticipated ones) are an integral part of a MC system.

6. General Discussion

6.1 Theoretical Implications

In all studies, we found the similar pattern of reduced creativity of self-designs after community feedback was presented to a focal decision-maker. Thus, although previous research advanced our understanding about why consumers use MC systems and how self-designable products increase object valuations, our results have shown that this new dimension of consumer-to-consumer interactions significantly alters the previously isolated decision processes of consumers in a product customization context. In particular, we found that consumers tend to avoid more extreme self-designs and that the probability mass of attribute distributions significantly shifts toward intermediate designs that are less ostentatious and assumed to be only moderate in their self-expressing function. Furthermore, although consumers tend to integrate external community feedback into their final self-designed product, we have shown that these shifts toward the mass decrease consumers' satisfaction with the self-designed product and is mediated by the complexity of the decision process as well as decision uncertainty. Thus, our results suggest that the value of self-designable products may not only be a function of the choice of novel and unique attributes, their combination and the effort a focal consumer has put into the self-design procedure (Franke, Schreier, and Kaiser 2010), but may also be considerably influenced by the provided feedback of other individuals around them. Consumers may prefer to own socially accepted products with less optimal value propositions but not necessarily vice versa.

Overall, our results underlined that failing to account for the possible impact of external influence on consumers' final self-design choices may not lead to correct theoretical as well as practical conclusions. Since past studies combined self-designable products and online community interactions, we have shown that it will be important to account for any intended or unintended community effects when designing and running studies in such socially enriched research contexts. This is particularly important as past research stressed the notion of the value driver of uniqueness in MC and that self-design procedures are means to differentiate the self from others as well as owning unique products may generate idiosyncratic value to its possessor (Franke and Schreier 2008; Fromkin 1970).

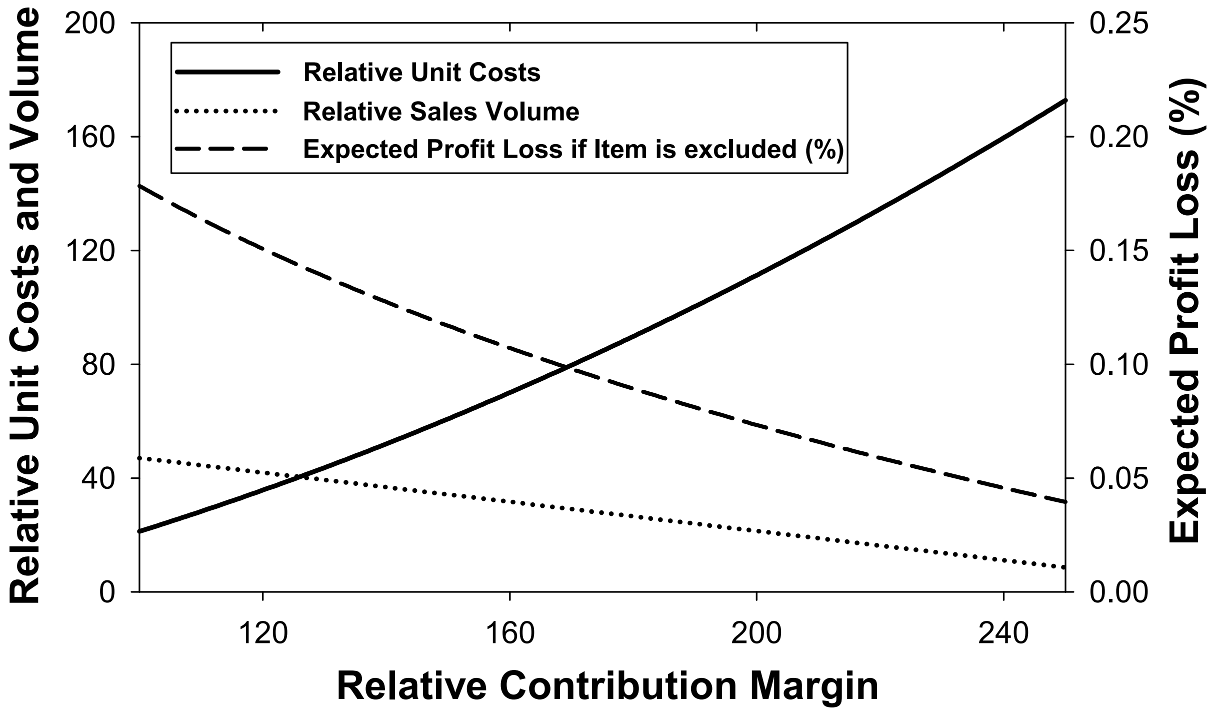
Building on the important work of the last two decades in MC related research, our results highlight the importance of adding the social dimension in preference formation and deviation into the context of self-designable products.

6.2 Practical Implications

From a practical point of view, our results finally raise the question of how converging consumer preferences are related to the broader level of the portfolio profitability of a company. Our results suggest that the heterogeneity and variability of individual self-designs may not increase but rather decrease during the phase of social interactions. This would in turn call for a more selective minimization and not maximization strategy regarding the number of attributes for modern MC systems since increased attribute variety is strongly associated with increasing complexity costs and costs for production and logistics systems. Thus, if extreme attributes are less frequently sold and offer only a rather low profit contribution, albeit higher prices, it is important to think about the economic consequences of consumer conformity on the overall assortment size.

Based on additional financial data of the car manufacturer of our field study, we assessed possible profitability changes as a function of the actual assortment size. In particular, we assessed the change in assortment profitability based on the exclusion of the more extreme attributes at the lower and upper quartile. Herein, we gained access to the contribution margin, sales volume as well as fixed cost per attribute to conduct additional simulation studies. For example, Figure 9 shows that the increase in the attributes' contribution margin is related to a strong increase in product-related fixed costs while the overall sales volume is rather low. In addition, the dashed line also shows that although excluding one of the upper-end attributes may result in stronger negative effects on total revenues due to its high contribution margin, the effect on profit loss is fairly low because of the disproportionate high costs. Thus, it is important to focus not only on the contribution margin of attributes but also on the fixed cost adjusted profit contribution since the profit elasticity conditional on the ratio of the contribution margin and unit profit is fairly high ($\text{Beta}_{\ln(\text{contribution margin / unit profit})} = 1.619$, $t(8) = 2.648$, $p < .05$).

Figure 9: Relationship between Costs, Volume, and Expected Profit Loss after Portfolio Optimization



Note—All "relative" variables were calculated as a ratio with respect to the smallest attribute due to legal restrictions of our project partner for publishing the data. Thus, one attribute is fixed at a certain value (e.g., 100), and deviations must be interpreted in relative terms as a percentage increase or decrease with respect to the base level (e.g., an attribute with a relative unit cost of 120 is 20% higher compared to the base attribute with relative unit costs of 100).

To assess the possible effects of a portfolio restructuring, we conducted additional Monte Carlo simulations and sensitivity analyses. We modeled the effect of excluding two attributes at the upper end of the attribute assortment and analyzed the effects of shifting demand on lower attributes conditional on production constraints and possible increases in price, subject to highly inelastic, isoelastic, and high price elasticity of demand. We solved the underlying optimization problem of finding the optimal and profit-related assortment structure conditional on production and pricing constraints (additional production capacity < 10% and maximum price increase < 5%), by using linear programming techniques. We found that only slight adjustments of either price or volume increase or both (e.g., overall price increase of 3.9% while production volume is kept constant or by a 2% price increase with 3.9% increase in production capacity) could compensate the expected profit loss of excluding both upper-end items. We estimated all these effects rather conservatively. For example, we did not explicitly model the additional loss in complexity costs that arise in a complex MC system, such as complex production planning, high coordination costs in production and logistics, capital lockup or storage costs of many variants, high repair costs, and hidden service costs on the sales and after sales level.

Overall, our results offer important practical implications regarding the consequences of an increase in consumer conformity on the optimal assortment size in MC systems, and that companies may provide less attributes while realizing equal profitability and also making complex decision processes considerably less effortful for consumers. Furthermore, and with reference to the consumer, our experimental results have provided empirical evidence, that offering less interaction between consumers may finally increase consumer welfare and reduce the perceived complexity of the decision process and decision uncertainty as well as avoiding the negative influence on consumers' final product satisfaction. Thus, our results suggest that reducing the possibility for social comparisons within the self-design process may have positive implications for consumer welfare and product satisfaction.

6.3 Limitations and Future Research Directions

We conducted all our experiments within highly socially visible product categories. Although all our results point in the same direction and similar effects for related product categories might be reasonable (e.g., fashion or consumer electronics), other, less socially visible, product categories (e.g., financial services or personal care products) need further investigation. Although it seems intuitive to hypothesize a positive linear relationship between the degree of social visibility and the strength of our revealed effects (e.g., the strength of community feedback on deviations in consumers' self-designs), it is likely that the interaction between social visibility of the product category and the respective domain complexity is important for further understanding of decision-making in the real and virtual world. While low product complexity and high social visibility (e.g., our jewelry case) can reveal strong effects on individual decision-making, the same effects may arise for domains of low social visibility and high complexity (e.g., banking, insurance, etc.) but for different reasons due to other individually relevant dimensions (e.g., impression management through certain products vs. anxiety of long-term financial disadvantages by choosing the wrong financial product).

Furthermore, it would be interesting to test if the low product satisfaction of influenced consumers remains constant over time. It might be suspected that because of further interactions with other feedback providers, consumers may adjust their previous negative valuation. On a more fine-grained level, it would also be important to see if this possible effect might be a function of the strength or intimacy of their relationship. In a similar vein and on a more global level for the area of marketing research, it would also be interesting to analyze if and how social interactions with others may moderate individuals' feelings of satisfaction as well as dissatisfaction. To the best of the authors knowledge, there is no such research that particularly focused on these underlying social mechanisms on consumers' feelings of regret or dissatisfaction dependent on the given social support (or disapproval).

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Article II

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When Social Media Can Be Bad For You – The Influence of Online Community Feedback on Consumers Perceived Self-Esteem, Decision Certainty and Probability To Buy

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Abstract

Mass Customization technologies are increasingly becoming social and allow for inter-individual exchange processes such as community-based configuration systems online. But while companies foster community interactions and open their configuration systems, it is not clear (1) how virtual interactions influence consumers' perceived decision certainty when receiving feedback on a self-designed product, and (2) how these usually anonymous feedback processes may directly affect consumers perception of their own selves. We applied an experimental research design in an online community environment and provide evidence that anonymous feedback negatively affects consumers perceived decision certainty and that this decreased certainty is strongly related to consumers purchase probability. Moreover, we revealed new theoretical and practical insight that feedback effects can directly and negatively influence individuals' perception of self-worth and that common affirmation strategies may backfire and finally result in considerably lower decision certainty.

Keywords: Mass Customization, User Self-Design, Consumer Decision Making,
Social Influence, Self-Esteem, Online Experiment.

1. Introduction

The last few decades of information systems (IS) research considerably advanced our understanding of why, how, and when individuals join virtual communities (e.g., Lakhani and Von Hippel 2003; Lin 2006; Preece et al. 2004), what motivates individuals to contribute knowledge within these often anonymously online environments (e.g., Ma and Agarwal 2007; Wasko and Faraj 2005), and the way these interactions may influence individuals' offline behavior (e.g., Bickart and Schindler 2001; Kavanaugh et al. 2005). In addition, research efforts in recent years have underlined the major importance of examining the degree of social influence on individual decision, consumption, and usage behavior (e.g., Agarwal et al. 2008). Thus, although these virtual interactions may lack important social cues of real social interactions, they nevertheless affect our everyday decisions with significant influence on individual behavior and economic decisions (e.g., Kleinberg 2008; Kozinets 2002; Mayer 2009; McAlexander 2002).

A new direction within this latest socially enriched IS research is related to the integration of user communities within consumer self-design processes (e.g., Franke et al. 2008; Wu 2010). Understanding how virtual peer influence affects individual decision behavior is of fundamental importance, as companies such as Threadless or Lego not only offer highly sophisticated toolkits for user self-designs but also motivate users to post their configurations within the community and revise configurations with other users (see http://www.threadless.com and http://www.designbyme.lego.com). However, although we see increasing growth of these community-based business models, it remains unclear: (1) how virtual interactions influence individuals' decision certainty during self-design procedures, and (2) how these usually anonymous feedback processes may directly affect individuals' perception of their own selves.

We address these research questions by applying an experimental research design in an online community environment. This experimental setting allows us to influence and manipulate the dimensions in question directly (e.g., the difference between the initial user preference and community feedback) while controlling for potentially confounding other factors in a real setting (e.g., different content and nuances in the tone of a message). We programmed an online community framework that allowed us to systematically manipulate the information we presented to participants.

Overall, our results show that anonymous feedback significantly influences consumers' decision behavior. In particular, we found that the more individuals deviated from their initial self-design, the lower their perceived decision certainty. Most importantly, individuals' deviation was significantly moderated by their degree of self-esteem. A follow-up study revealed new theoretical and practical insight that feedback effects can directly and negatively influence consumers' perception of self-worth and that common affirmation strategies may backfire and result in considerably lower self-esteem and certainty.

2. Theoretical Background

2.1 Online Social Interactions and Individual Decision Behavior

The development of technologies allowing users to connect with each other and share their ideas, discuss various personal topics of everyday life, or search for information for planned purchases led to the broad development of virtual online communities (e.g., Brown et al. 2007). In this regard, the first stream of research helped to understand users' general motivation to engage in these types of virtual environments (e.g., Lakhani and Von Hippel 2003; Preece 2001). In addition to this motivational view of the first years of online community research, the research efforts of the following years particularly focused on the inherent business value of these networks, such as increasing consumers' brand loyalty (e.g., McAlexander et al. 2002; Thompson and Sinha 2008), generating new product ideas (e.g., Nambisan and Baron 2007), implementing community-based customer support (e.g., Dholakia et al. 2009) as well as finally influencing consumers' purchase intentions (e.g., De Valck et al. 2009; Kozinets 2002).

However, although past research enriched the motivational aspects of interacting in virtual systems and assessed the economic potential of harnessing social networks from a business perspective (Kane et al. 2009), we understand less about the psychological influence of these interactions and respective feedback effects through computer-mediated interactions (De Valck et al. 2009). Although we better understand what drives consumers to participate in online communities and their intention to share ideas with others, what we can expect if consumers receive direct feedback on their ideas, the products they design and want to share with others, or their opinions on given topics is far less understood (Moreau and Herd 2010). For example, past research has shown that receiving community feedback when designing mass customized products increases customers' satisfaction as well as individual willingness to pay (Franke et al. 2008). In particular, Franke and his colleagues revealed empirical evidence that the influence of external and anonymous users had considerable positive effects on consumers' decision outcome. Unfortunately, less known is consumers' reaction to distant and probably non-confirming feedback. Although previous research revealed evidence that consumers may heavily discount too-deviant feedback (Yaniv 2004), recommendations from hardly known others can significantly affect individual decision behavior (e.g., Chevalier and Mayzlin 2009; Dellarocas 2003). Thus, although we may conclude that informational influence may hold in virtual worlds, the direct effect in terms of a normative influence on final choice, the satisfaction with this choice, and the influence of this external feedback on the individual are far less understood.

The last aspect regarding others' influence on one's perception of oneself through anonymous computer-mediated communication is of interest on a broader level. Since it follows that informational cues are inherently multidimensional (e.g., Stern 1994), individuals have to process at least two dimensions of information: a neutral informational dimension that is context specific and intended to help the receiver in making a better decision (i.e., helping to design a respectable product) and the implicit judgmental dimension as it inherently carries more or less implicitly the sender's personal preferences and values in contrast to the receiver (i.e., something is not good enough and has to be optimized). As a result, irrespective of the sender's initial intention, the decisional context of the receiver, and her personal view regarding the decision in question, the receiver's impression of herself may change (perhaps also regarding the sender). Since individuals exchange information, comment on each other, and give feedback in nearly every virtual online setting (forums, discussion boards, blogs, social network sites, shopping sites with comment functions, etc.), better understanding of how computer-mediated, usually anonymous, information may affect users' inner representation of themselves and their individual self-design choices afterwards is needed.

This is of particular interest for the domain of self-designable products in a mass customization context since it is usually assumed that the increasing heterogeneous demand for customizable products is based on the increasing pursuit of individuality and distinctiveness on the individual level (Franke et al. 2008). Thus, we would suspect that consumers are less prone to external social influence in a virtual setting since it is generally assumed in the marketing literature that consumers design these products according to unique preferences (e.g., Randall et al. 2007). Nevertheless, the business practices and new technological developments of the last few years have shown that modern self-design procedures are increasingly becoming social and customization technologies are becoming permeable (e.g., Wu 2010), explicitly underlining the intertwining of technological and social networks (Agarwal et al. 2008).

Overall, researchers have shown that community members exchange information in terms of directly commenting on posts (e.g., Lampe and Johnston 2005), rating individual user designs (Franke et al. 2008), or evaluating and refining ideas and the like (e.g., Franke and Shah 2003). Thus, we may also link these findings to the research stream that these virtual online interactions may have a strong influence on future participation and future success for the respective community itself (Bateman et al. 2010). For example, previous research revealed considerable evidence that inter-individual comments within the community affects the participation probability on the individual level and the future success of the respective community in general (e.g., Vasalou et al. 2008).

2.2 Protective Adaptation and the Role of Self-Esteem

In addition to these past IS- and marketing-related research findings, the past decades of social and personality psychological research can be related to this stream of research to explain the underlying psychological dimensions of these previously discussed influence processes (e.g., Gilbert et al. 1998). On a general level, research has shown that individuals regularly apply unconscious coping strategies that protect individuals from possible external influences. In particular, people are strongly motivated to adapt to protective adaptation strategies and construe mentally driven re-interpretations of situations to lessen the effect of potentially threatening information on individuals' self-worth (e.g., Koole et al. 1999). This strong human motivation helps to cope with the numerous threats and failures of everyday life (e.g., Schmeichel and Martens 2005). For example, people refuse to adopt threatening health information (Sherman et al. 2000), perceive themselves as responsible for positive but not for negative outcomes (Taylor 1983), and strongly discard distant types of feedback that are systematically different from their own (Yaniv 2004).

In this regard, Steele's (1988) seminal work established the so-called theory of self-affirmation and provided a theoretical framework for these previous effects. The fundamental argument of this theory is that individuals are willing to pursue a positive view of themselves and are adaptive in maintaining and protecting their perceived self-integrity. In particular, he states that individuals strive to "maintain a phenomenal experience of the self […] as adaptively and morally adequate, that is, as competent, good, coherent, unitary, stable, capable of free choice, capable of controlling important outcomes" (p. 262). As a result, individuals' motivation to protect themselves can lead to defensive processing strategies by which external information is strongly discounted (e.g., Kunda 1990).

The role of individuals' self-esteem has become increasingly important in this stream of research (e.g., Steele et al. 1993). For example, Steele et al. (1993) showed that individuals with a high degree of self-esteem have stronger protective resources to cope with threatening information than individuals with lower self-esteem (see also Nail et al. 2004). Thus, although past research underlined individuals' broadly applied self-protective strategies, examining them in the context of computer-mediated communication within the field of IS research and explaining feedback effects on the individual level in virtual environments will be of interest.

Furthermore, lay intuition about how to encourage users within a community who may receive less positive feedback from other users—which may lead to significantly less participation in the future (e.g., Lampe and Johnston 2005)—could lead to simple enhancement strategies to motivate users to join the community and participate again. In this regard, recent findings in the area of the previously discussed self-affirmation theory suggests that affirmations related to the threatening act can result in backfiring effects in terms of increased resistance and dissonance (Sherman et al. 2009). Thus, from a practical as well as theoretical point of view, examining how to change users' motivation and self-perception with applied affirmation strategies will be elusive.

3. Development of Hypotheses

Since we have initially discussed the current state of research and relevant findings, we will now discuss our derived hypotheses and the underlying conceptual framework. We will derive our hypotheses directly from existing research findings within the relevant research streams and will test our hypotheses systematically in two subsequent studies.

In general, we will examine external computer-mediated and simulated social influence on users' individual decision behavior. In this regard, Tversky and Kahneman (1974) highlighted the fundamental role of anchoring and adjustment effects in human decision behavior. In essence, numerous studies on individual decision behavior revealed empirical evidence that exposing individuals to a decision-relevant as well as non-relevant reference point leads to the subtle assimilation of final choices toward this previously considered anchor (e.g., Strack and Mussweiler 1997). Most importantly, it has been shown that these anchoring effects influence a tremendous variety of decisions, ranging from consumers' price decisions and legal judgments of attorneys or judges to general probability assessments, influencing experts as well as non-experts, and still remain if people are informed about these biases (e.g., Kahneman 1992).

This leads us to the prediction that also consumers in a choice situation will adapt their final decisions to the reference point of an external community recommendation. In particular, we predict that the deviation from an initial choice is determined by the distance between the individual's initial preference and the deviation of the community recommendation. Thus, we predict:.

> **H1:** The greater the distance of an external recommendation from the user's initial self-designed product, the greater the revision of the initial choice.

Second, whether possible preference revisions may systematically influence consumers' degree of perceived certainty is not clear. Extending Moreau and Herd's (2010) recent findings, we predict that social comparison processes induce external ego-threatening information on individuals' initial configuration and makes the weighting of external feedback and already revealed initial preferences increasingly mentally exhausting. Thus, balancing one's own preference as well as a deviant external community recommendation may result in an increase in discomfort and feelings of inconsistency. Based on the robust findings of previous inconsistency theories (e.g., Higgins 1987), we predict that this revealed dissonance effect will reduce the perceived decision certainty of the focal consumer.

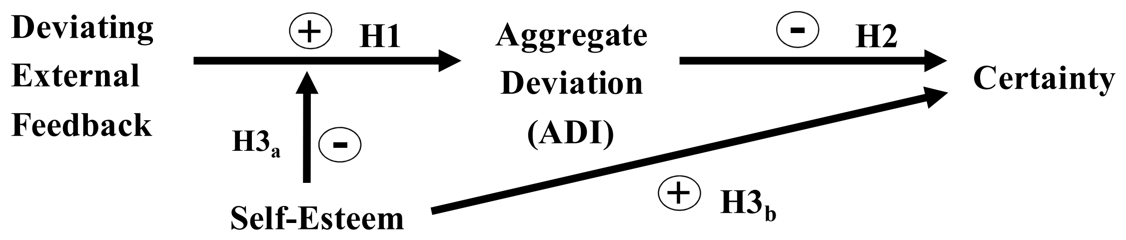
H2: The higher individuals' deviation from their initial self-design, the lower their decision certainty with the self-designed product.

According to the previously discussed findings in the domain of social and personality psychology, individuals with more positive views of themselves may have more resources to resist external influences (Steele 1988). We adapt these findings to the virtual context of computer-mediated influence processes and predict that individuals are less prone to being influenced by externally induced community recommendations in the case of higher self-esteem and will be more certain with their self-designed product irrespective of previous deviations. Thus, we predict:

H3: The higher individuals' self-esteem, (a) the lower the influence of external feedback and (b) the higher the decision certainty with their self-designed product.

Figure 1 illustrates the relationship of these hypotheses, the respective measures, and the predicted direction of influence. These particular hypotheses will be tested as part of study 1.

Figure 1: Framework of Hypotheses for H1 to H3 of Study 1 (Moderated Mediation Model)



Thus far, we have assumed that individuals' perception of self-worth is a stable personality trait measured before any experimental manipulation. What is less clear so far is what we can expect regarding the direct influence of distant external feedback on individuals' self-perceptions. With reference to the previously noted theories of inconsistency (e.g., Higgins 1987), a variety of studies have shown that aligning incompatible self-beliefs with external expectations can lead to strong emotional vulnerabilities (e.g., Aronson 1968). In particular, perceiving the discrepancy between the current state of the self (in terms of attitudes or behavior (e.g., choices)) and the current state of others has been found to be associated with individual discomfort and feelings of resentment (Higgins 1987). Building on these previous findings of a revealed negative influence of perceiving this incompatibility between the self and consumers' social environment, we predict that receiving deviant community recommendations will lead to a decrease in self-evaluations and perceptions of self-worth:

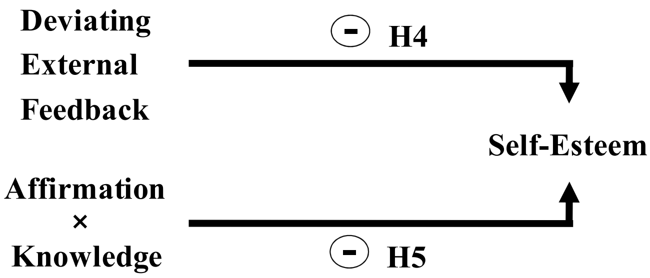
> **H4:** The higher the distance of externally induced feedback, the lower individuals' subsequent perception of self-worth.

Finally, as externally induced feedback may reduce individuals' perceived certainty and perception of self-worth, we examine strategies for consumer self-affirmation in a virtual environment. According to past research, positively affirmed individuals may experience increased certainty and self-esteem (Correll et al. 2004). Thus, giving positive affirmation leads to reasserting individuals' perceived self-integrity when coping with threatening information (Fein and Spencer 1997). However, it has been shown in the area of attitude change that the importance of the affected domain of interest is an important moderator of the relationship of external stimuli and attitude change (Boninger et al. 1995). In the area of effective self-affirmation, Sherman and colleagues (2009) recently showed that affirming individuals in areas of high personal importance that are highly salient to participants and related to the decision context led to negative affirmation effects. In essence, the intended positive affirmation resulted in an increase in availability of participants' inconsistent behavior (see also Crocker and Park 2004). For example, a mother who is highly experienced as a teacher and was influenced recently to try new educational methods will perceive a larger threat to her self-perception when reminded about applying these methods that are not considered as central in her view of educational practice, due to the interaction of the increased salience of the respective domain and her own level of expertise. As a result, we predict that affirming individuals positively will backfire and result in a negative influence on self-worth for individuals with high domain knowledge due to the high personal relevance for those individuals and the process of reminding them of their previous inconsistent behavior. Thus, we finally predict:

H5: Positive affirmation for high-knowledge users will result in a backfiring effect in terms of a lowered degree of self-worth.

Figure 2 illustrates the relationship of both hypotheses 4 and 5, their respective measures, and the predicted direction of influence. Note that hypothesis 5 will of course test for the respective main effects, but the proposed interaction and its predicted negative effect on self-esteem are primarily of theoretical interest.

Figure 2: Framework of Hypotheses for H4 and H5 of Study 2



4. Empirical Studies

To test our derived hypotheses, we conducted a series of field experiments in a systematically manipulated community framework. In the next section, we introduce the general study design first and present the details of our realistically framed experimental setting. As part of study 1, we focused (1) on the general influence of external feedback on individual decision behavior and (2) the moderating role of individuals' perception of self-worth. Thereafter, as part of study 2, we examined the (1) direct effect of external influence on individuals' self-esteem and (2) evaluated strategies for consumer self-affirmation.

4.1 Study Design and Community Framing

To manipulate inter-individual interactions and choices, we developed and programmed a community framework where all controlled experiments were run. Since we programmed the back- and frontend of our community platform, we were able to systematically vary the manipulated type of feedback with simple java code and stored participants' answers in SQL databases during the time of the experiment. We implemented our community framework as a virtual shopping environment with a jewelry configurator as a specific application. We chose the jewelry domain as our experimental product category due to its high social visibility. Our main interest is to test social influence patterns in an identity-signaling product category that can be easily perceived by others (Berger and Heath 2007). Furthermore, Eagly and Carli's (1981) meta analysis of gender differences in influenceability revealed no divergent effects when controlling for surveillance of the respective situation.

Within the member area, participants were introduced to the general procedure of the study and were presented our self-developed and manipulable Flash-based product configurator to tailor an individual pair of earrings, consisting of 188 items overall in four categories (ear hook, small, medium, and large jewelry items) that were carefully pre-tested with 32 participants and confirmed to be the market-wide dominant earring jewelry items at the time of the study. During the configuration process, participants chose a jewelry item in each of the four presented categories. Figure 3 shows the final frontend of our programmed community environment.

Figure 3: Frontend of Community and Flash-Based Jewelry Customizer

In general, we applied a two-step approach for all experiments as follows: in the first phase of all experiments, participants designed their personal earring, answered several survey-based questions, and were informed that one of our community members would be randomly chosen to provide individual recommendations for the participants' initial configuration. After a time lag of 48 hours, participants received an email and were re-invited to look at their community feedback within the member area and were given the opportunity to re-configure their first design if wished. Both studies were strictly incentive compatible as participants were informed that they would take part in a raffle to win their self-designed earring.

4.2 Study 1 – Virtual Influence Mechanisms and the Protection Role of Self-Esteem

As part of the first study, we will examine our previously derived hypotheses 1 to 3. In particular, we will assess the influence of deviating community recommendations on participants' final deviation with regard to their initial configuration of a self-designed earring (H1), the impact of possible subsequent deviations on consumers' perceived certainty (H2), and the moderating role of individuals' self-esteem (H3).

4.2.1 Experimental Design and Procedure

Participants were introduced to the study's general procedure and then presented to our Flash-based jewelry customizer to design their individual pair of earrings. After participants completed their self-design process, they answered a self-esteem scale (see the next section in further detail) and several demographic questions. At the end of the study, participants were told that their design had been forwarded to a community member and that they would receive individual feedback. Finally, participants were told that they would be re-invited automatically to participate in the second part of the study. We programmed a server script that automatically re-invited participants after 48 hours. To maximize the realism of our manipulations, participants were primed after their first configuration by answering questions about their favorite color, fashion preferences as well as eye and hair color that would be also forwarded to a community member. In the second phase of the experiment, participants logged in to the member area and read their recommendation on the start page. Participants received a standardized and anonymous feedback message without any specific arguments for or against their first configuration; we manipulated only the presented recommendation based on individuals' choices in the first phase.

Participants were randomly assigned to one of two groups: the first group received a recommendation that was only slightly different from their first choice and changed by only one jewelry item per category. In particular, each jewelry item in all four categories (ear hook, small, medium, and large jewelry items) had a unique index value increasing from left to right. Participants in the low deviation manipulation received a recommendation that was changed by only one index value, whereas the high deviation condition skipped a minimum of 50% of the complete scale of the category. For example, if an individual chose item No. 2 of 10 possible items within the category, she received a recommendation of item No. 3 in the small deviation condition and item No. 7 in the high deviation condition. We applied an algorithm that automatically calculated the respective differences within each category and presented participants with the systematically manipulated recommendation at the beginning of the second phase. A total of 792 female participants were recruited from an online consumer panel to take part in the study (M_{Age} = 37, SD = 10).

4.2.2 Operationalization and Measurement

To measure the degree of distant feedback on choice, we applied a weighted Euclidean distance measure according to Shocker and Srinivasan (1974) and classical preference modeling procedures, since (1) positive and negative deviations from the initial configuration and (2) the inter-individual heterogeneity of the category importance have to be considered, e.g., low deviations within highly important categories and vice versa. Thus, our algorithm estimated the Euclidean distance between the initial and final decision first and then weighted this difference with an individual weighting parameter that corresponded to the participant's stated importance of each category. All individual weights sum up to one. We will call this metric in the following the aggregate deviation index (ADI):

$$ADI_i = \sum_{c}^{C} \sqrt{(\tau_{ic}(t_1) - \tau_{ic}(t_2))^2} \times \omega_{ic}$$

with the choice of item τ by individual i in category c, at time t_1 and t_2 and the individual category importance ω. Furthermore, we measured individuals' perceived certainty with the self-designed product with reference to Argo, Dahl, and

Manchanda's (2005) introduced scale. The latent construct was condensed by a single factor that accounted for 88% of explained variance with high scale consistency ($\alpha = .93$). Individuals' degree of self-esteem was measured according to Rosenberg's (1965) scale with positive and negative self-esteem assessment and a total of 74% of explained variance and appropriate scale reliability ($\alpha = .82$).

4.2.3 Manipulation Check

We carefully evaluated the effectiveness of our feedback manipulation. As expected, participants perceived the feedback of the anonymous community member within the highly deviant manipulation as significantly different from their initial configuration ($M_{High\_Deviation} = .22$ vs. $M_{Low\_Deviation} = -.20$, $t(790) = 5.998$, $p < .001$). Thus, the effectiveness of our experimental manipulation was confirmed.

4.2.4 Results

To test our specified hypotheses, we conducted a moderated mediation analysis to measure all dependencies at once and to ensure a higher statistical power (Preacher et al. 2007) (note that every specified hypothesis could be tested by applying linear models or ANOVAs but with the disadvantage of increasing a type II error of statistical testing). As expected, we found a significant effect for the degree of deviation from individuals' initial preference by presenting highly distant feedback ($Beta_{\Delta Preference} = .05$, $t(788) = 3.547$, $p < .001$). Thus, although participants designed their individual earring in the first phase, introducing anonymous and systematically manipulated feedback led to significant changes in the participants' final choice, supporting hypothesis 1. Furthermore, this increased deviation resulted in a significant decrease in individuals' perceived certainty with their decision ($Beta_{ADI} = -.16$, $t(787) = 3.925$, $p < .001$). Hence, hypothesis 2 is statistically supported as well. In general, the path from external deviant feedback to individuals' perceived certainty was found to be mediated by individuals' degree of deviation (ADI) as indicated by a significant Sobel test ($z = -3.268$, $p < .05$). Overall, hypotheses 1 and 2 support our hypothesis that although individuals deviate from their initial choice and no social costs or relevant social ties were present, the individuals' free will of deviation resulted not in an increase of perceived certainty but rather in a final decrease. This recalls our theoretical discussion of possible self-affirmation strategies in a virtual context, and we will address this point in the second study in further detail. Most importantly, and as predicted, the moderation of individuals' self-esteem on ADI was significant as well ($Beta_{\Delta Preference \times Self\ Esteem}$ = .03, t(788) = -2.498, $p < .05$). This supports our theoretical argument that individuals' self-esteem operates as a corrective procedure within influence processes and leads to stronger reliance on individuals' initial preference. Thus, hypothesis 3a is empirically supported. Furthermore, we also found the predicted positive effect of individuals' self-esteem on consumers' perceived certainty ($Beta_{Self\text{-}Esteem}$ = .35, t(787) = 4.396, $p < .05$), confirming our discussion that individuals' perception of self-worth may function as a "psychological immune system", protecting individuals from external influence processes. Thus, hypothesis 3b is finally supported as well.

Table 1: The Mediational Influence of Aggregate Deviation on Perceived Decision Certainty and the Moderating Role of Consumers' Self-Esteem

Predictor	**Beta**	**SE**	**t-Value**	**p-Value**
Aggregate Deviation (ADI) (Mediator Model)				
Constant	.539	.066	8.214	< .001
Δ Preference (Δ Pref)	.046	.013	3.547	< .001
Self-Esteem (SEST)	.093	.069	1.352	.177
Δ Pref × SEST	-.034	.014	-2.498	.013
Perceived Decision Certainty (Dependent Variable Model)				
Constant	.115	.080	1.440	.150
ADI	-.161	.041	-3.925	< .001
Δ Pref	.001	.015	.056	.955
SE	.348	.079	4.396	< .001
Δ Pref × SEST	-.009	.016	-.602	.548

4.2.5 Discussion

Overall, our findings of the first study revealed new insight that anonymous computer-mediated feedback leads to significantly deviating choice behavior. This effect occurred without particular community norms, social intimacy, or anticipation of any future social costs—just setting a community recommendation as a reference point alters individuals' choice behavior and perceived certainty with their self-designed product. This generalizes (1) the application of traditional social influence and anchoring studies within a virtual context and (2) the direct influence of virtual interactions on individual decision making. The latter is of major importance since De Valck et al. (2009) underlined the caveat of previous studies that relied on retrospective and self-stated measures regarding community influence on individuals' decision behavior.

As part of the next study, we will examine the direct effect of external feedback on individuals' perception of self-worth and will test strategies for user self-affirmation in order to deal with the drawback of decreasing certainty after relying on external recommendations.

4.3 Study 2a – The Direct Influence of Community Feedback on Self-Esteem

Study 1 revealed new empirical evidence that individuals are prone to systematically deviate from their initial preference after receiving externally induced and manipulated feedback on their initially self-designed product. In accordance with our predictions, this effect was significantly moderated by users' degree of self-esteem. In the next study, we will apply generally the same study design as before but will explicitly measure the effect on users' perception of self-worth in the second phase of the experiment. In particular, we will assess the influence of external community feedback on individual self-esteem by applying a pre-feedback measure in the first phase and a post-feedback measure in the second phase. This allows us to study the effect of community influence on individuals' self-perception (H4) and possible affirmation strategies on the individual level (H5).

For this second study, a total of 283 female participants were recruited from an online consumer panel (M_{Age} = 36.5, SD = 10).

4.3.1 Experimental Design and Procedure

Similar to our first study, participants designed their initial earring, answered the self-esteem scale, and were automatically re-invited after 48 hours. After the participants received their manipulated recommendation (the same manipulation of low vs. high deviation as in study 1), they were given the opportunity to reconfigure their product if needed. Subsequent to possible reconfigurations, participants were randomly assigned to one of two groups: an experimental group that received self-affirming cues with an affirming text message that assured individuals' perception that they had designed a beautiful configuration and was emotionally enriched by pictorial cues, underlining individual happiness and freedom. In contrast, the second group was set as control group and received no information at all. At the end of the experimental manipulations, participants answered the self-esteem measure again as well as several other scales (see below in further detail).

4.3.2 Operationalization and Measurement

We measured the degree of self-esteem based on the same scale as in study 1. Participants answered the respective items before (the pre-feedback measure of the first experimental phase) and after our manipulations (the post-feedback measure within the second phase). The positive and negative items of the self-esteem scale within the first phase accounted for 66% of explained variance and were aggregated by a single measure with appropriate scale reliability ($\alpha = .75$). The post-feedback measure of self-esteem of the second phase revealed similar and consistent results (70% of explained variance, $\alpha = .77$). Consumers perceived decision certainty measure was based on the same items as in study 1, and the scale consistency was confirmed as well (87% of explained variance, $\alpha = .92$). In addition, we measured individuals' degree of domain knowledge according to Flynn and Goldsmith's (1999) scale. The construct was condensed by a one-factor solution with a high 81% explained variance and appropriate reliability ($\alpha = .88$).

4.3.3 Manipulation Check

Again, we evaluated the effectiveness of our feedback manipulation before analyzing the data. As expected, participants perceived feedback from the anonymous community member of the highly deviant manipulation as significantly different from their initial configuration ($M_{High\_Deviation} = .20$ vs. $M_{Low\_Deviation} = -.21$, $t(281) = 3.520$, $p < .01$). Thus, the effectiveness of our experimental manipulation was confirmed again.

4.3.4 Results

As part of hypothesis 4, we predicted that external feedback will reveal a negative influence on individuals' perception of self-worth, confirming the notion that highly distant feedback contains an implicit psychological threat to the initial preference of a decision maker. To test this hypothesis, we specified a multiple mediation model. As expected, our results revealed empirical evidence that anonymous, distant feedback—without stating any reasons regarding the participants' first choice—revealed a strong and negative influence on individuals' perception of the self ($Beta_{Self\text{-}Esteem\_post} = -.26$, $t(279) = -2.156$, $p < .05$). Note that both groups were not statistically different from each other when tested for differences in the pre-feedback measure in the first phase ($Beta_{Self\text{-}Esteem\_pre} = .02$, $t(279) = .198$, $p > .83$). This effect emphasizes that (1) anonymous virtual feedback can significantly decrease individuals' self-esteem and, (2) as a result, may also influence relevant individual dimensions that are not directly related to the choice at hand. Thus, hypothesis 4 is empirically supported. Moreover, we also replicated the negative effect of ADI and the positive effect of self-esteem on consumers perceived certainty ($Beta_{Self\text{-}Esteem} = .20$, $t(279) = 3.614$, $p < .001$; $Beta_{ADI} = -.12$, $t(279) = -1.803$, $p = .07$). Overall, the total effect of the meditation model was significant ($z = 2.553$, $p < .05$), and contrasts for ADI and individuals' self-esteem revealed that the meditational effects were of equal strength (contrast ADI vs. self-esteem = .011, $z = .277$, $p > .78$).

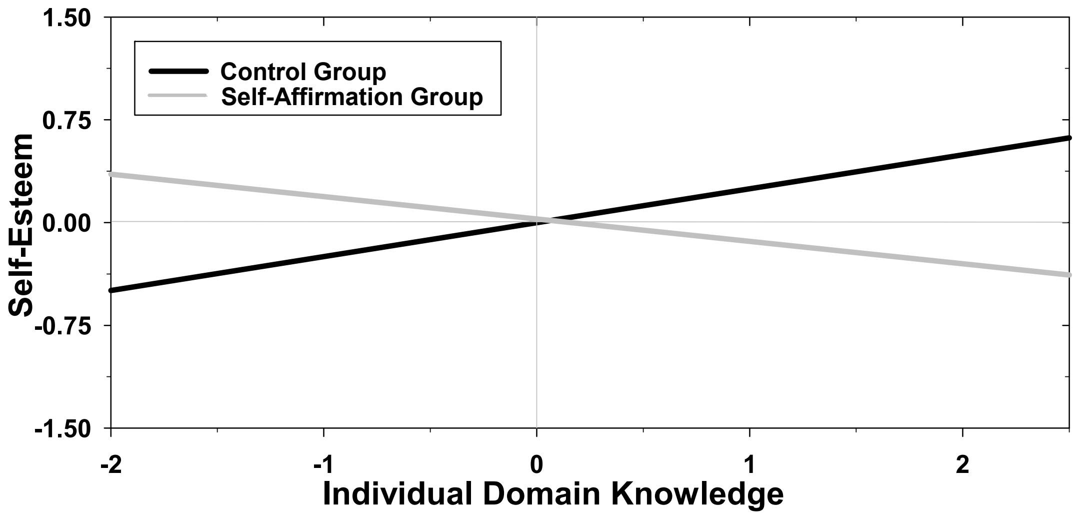
Table 2: The Mediational Effect of Distant Community Feedback on Decision Certainty through Consumers' Self-Esteem and Aggregate Deviation from the Initial Choice.

				Bootstrapping			
				Percentile 95% CI		**BC[c] 95% CI**	
	Beta	**SE**	**Test Statistic**	**Lower**	**Upper**	**Lower**	**Upper**
Direct Effects of IV on Mediators							
Self-Esteem (SEST)	-.261	.121	2.156**[a]	-	-	-	-
Aggregate Deviation (ADI)	.353	.102	3.444***[a]	-	-	-	-
Direct Effects of Mediators on DV							
SEST	.201	.056	3.614***[a]	-	-	-	-
ADI	-.119	.066	-1.803*[a]	-	-	-	-
Indirect Effects of IV through Mediators on DV							
SEST	-.052	.028	-1.856*[b]	-.122	-.024	-.131	-.001
ADI	-.042	.026	-1.605*[b]	-.115	-.001	-.118	-.002
Total Effect	-.094	.038	-2.453**[b]	-.181	-.024	-.185	-.024
Contrast of Indirect Effects							
SEST vs. ADI	.011	.038	.277[b]	-.076	.094	-.072	.099

*Note. *** p < .001, ** p < .05, * p < .10; (a) Estimated t-Value, (b), Estimated z-Value, (c) Bias Corrected Confidence Intervals.*

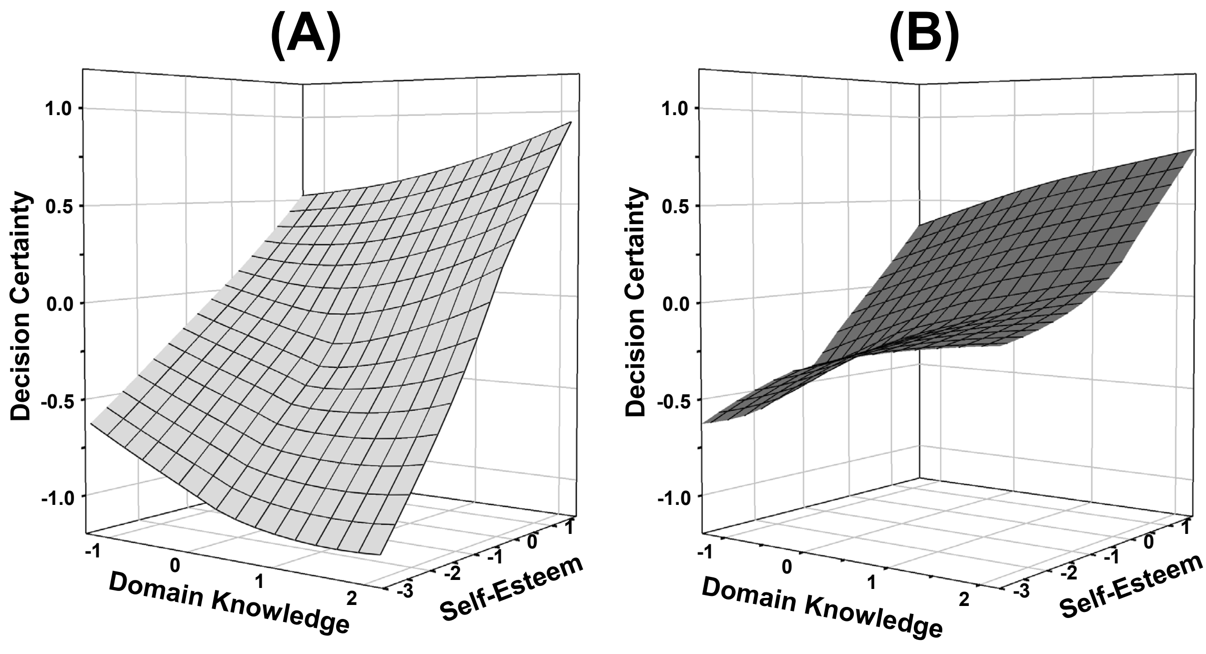
As part of hypothesis 5, we predicted that common affirmation strategies might backfire as a function of individuals' degree of domain familiarity. To test this hypothesis, we applied a linear model with individuals' self-esteem as the dependent variable and our experimental affirmation (affirmation vs. no affirmation) and individuals' degree of domain knowledge as the independent variables. As expected, the interaction term of affirmation × knowledge was statistically significant ($Beta_{Affirmation \times Knowledge} =$ .30, t(279) = 2.410, $p < .05$) and in the predicted direction: affirmed individuals experienced a negative effect on their personal perception of self-worth the higher their personal domain knowledge was. Both main effects alone had no significant influence on perceived self-worth ($Beta_{Affirmation} =$ .001, t(279) = .01, $p > .90$; $Beta_{Knowledge} =$ .14, t(279) = -.13, $p > .88$). This supports our prediction that lay beliefs about addressing and affirming important dimensions of individuals may backfire, as such beliefs remind decision makers of their susceptibility to external influence, making the inconsistent previous behavior highly salient. Thus, hypothesis 5 is statistically supported as well.

Figure 4: Backfiring Effect of Self-Affirmation as a Linear Function of Individuals' Knowledge



We also tested the extendibility of this backfiring effect by analyzing the combined effects (self-esteem and knowledge) on consumers perceived decision certainty with the self-designed product and the role of affirmation. We applied a linear model for all main effects and interactions, and in line with our previous results, the higher-order three-way interaction of affirmation × self-esteem × knowledge was marginally significant and again in a negative direction ($Beta_{Affirmation \times Self\text{-}Esteem \times Knowledge} =$ .23, t(275) = 1.882, $p = .06$). To aid interpretation of the three-way interaction, we illustrate the difference by showing the three-dimensional surface plots in Figure 5 (see West et al. (1996) for further recommendations). Both regression planes show that certainty is always positively associated with increasing self-esteem irrespective of knowledge ($Beta_{Self\text{-}Esteem} = .29$, $t(275) = 3.974$, $p < .01$) and that a larger positive increase in certainty for affirmed participants compared to non-affirmed participants occurred only in the region of low self-esteem with increasing knowledge ($Beta_{Affirmation \times Knowledge} = .30$, $t(275) = 2.426$, $p < .05$, holding self-esteem constant). However, and in line with our previous results, when both factors increased, the affirmed group achieved a lower overall certainty than the control group.

Figure 5: Backfiring Effect of Affirmation visualized in Smoothed Regression Planes for Self-Esteem and Knowledge on Certainty (A = Control Group; B = Affirmed Group)



4.3.5 Discussion

Overall, our results finally underlined that external feedback may directly influence individuals' perception of self-worth in a negative way. This is of major importance for at least two reasons: (1) virtual interactions and comments by often unknown users may significantly influence individual decision and participation behavior, and (2) since individuals strive to maintain a positive image of themselves, computer-mediated communication systems and increased interaction with others as part of an online community, distant project teams and the like, may be influenced within computer-mediated communication systems in a similar and predictable way as in real-life situations. Furthermore, strategies of providing affirmative information have to be reflected with respect to the importance of the domain for the respective individual. For example, directly asking an expert member of an idea-sharing community to participate in a new project while knowing that she received less positive feedback on her last contribution might be less effective compared to activating seemingly unrelated dimensions, such as checking other relevant domains that were stated within the user profile by providing a gift card for the respective service of interest or suggesting a project that is not closely related to the previous and probably negatively connoted project.

4.4 Study 2b – The Effect of Decision Certainty on Purchase Probability

4.4.1 Experimental Design and Procedure

In this final study, we are interested in how these previously discussed effects are related to consumers' probability to buy the self-designed product. In particular, based on the data of the previously reported study, we will now analyze if, and how, decision certainty is related to economic consequences in terms of the probability to buy the final product.

4.4.2 Operationalization and Measurement

At the end of the study, participants were asked to evaluate their final product and their interest to finally buy the self-designed earring. In particular, participants were informed that they can get the chance to buy the product if they are interested in, and that they have to state their personal probability to buy the product, ranging between 0% (unlikely) to 100% (definitely). This stated purchase probability was treated as the dependent variable in our following analyses, whereas decision certainty, self-esteem, and domain knowledge were treated as independent variables and were based on the same measures as reported in the previous study.

4.4.3 Results

We built four linear models with self-esteem (SEST), domain knowledge (KNOWL), and decision certainty (DECERT) to explain variation in consumers' purchase probability. Table 3 summarizes the final results. The baseline constant-only model revealed that the purchase probability in absence of any predictor was around 72%, confirming the high ecological validity of the study and provided attributes. Adding consumers' self-esteem was a significant predictor and positively associated with the probability to buy the self-designed earring ($Beta_{SEST} = 3.70$, $t(281) = 2.696$, $p < .05$) and this one-predictor model was significantly better than the constant-only model ($F(1,281) = 7.266$, $p < .05$). Consumers' domain knowledge was a significant predictor as well ($Beta_{KNOWL} = 6.58$, $t(279) = 4.498$, $p < .01$) and slightly reduced the influence of self-esteem on final purchase probability ($Beta_{SEST} = 3.62$, $t(279) = 2.720$, $p < .05$). Consumers domain knowledge increased the amount of explained variance by about 6% and was significantly better than the one-predictor model of self-esteem only ($F(1,279) = 10.554$, $p < .01$). However, when adding the strong predictor of consumers' perceived decision certainty ($Beta_{DECERT} = 14.93$, $t(275) = 12.125$, $p < .01$) the amount of explained variance increased by 34%, the influence of self-esteem became insignificant ($Beta_{SEST} = .64$, $t(275) = .567$, $p > .57$), and the overall model was significantly better than the previous two-predictor model ($F(4,275) = 40.212$, $p < .01$). Thus, the results finally show that consumers' perceived decision certainty is strongly related to the probability to purchase the self-designed product. In particular, a one unit increase in consumers' decision certainty resulted in an increase of about 15% percent points of final purchase probability, underlining the importance of our previously reported feedback effects on individuals perceived decision certainty.

Table 3: The Influence of Self-Esteem, Domain Knowledge, and Decision Certainty on Purchase Probability

Predictor	**Null Model**			**SEST Model**			**SEST & KNOWL Model**			**Full Model**		
DV = Purchase Probability	**Beta**	**SE**	**t-Value**[a]	**Beta**	**SE**	**t-Value**[a]	**Beta**	**SE**	**t-Value**[a]	**Beta**	**SE**	**t-Value**[a]
Constant	71.80	1.42	50.51***	71.80	1.41	51.07***	71.69	1.36	52.68***	71.25	1.15	62.13***
SEST				3.70	1.37	2.70**	3.62	1.33	2.72**	.64	1.13	.57
KNOWL							6.58	1.46	4.50***	3.69	1.24	2.98**
DECERT										14.93	1.23	12.13***
SEST × KNOWL								1.47	.92	.77	1.31	.59
SEST × DECERT										.47	1.14	.41
KNOWL × DECERT										.28	1.29	.21
KNOWL × DECERT × SELF										-.29	1.40	-.21
F-Statistic	---			7.27**			9.62***			29.42***		
R^2	---			.03			.09			.43		
F-Test Nested Models[b]	---			7.27**			10.55***			40.21***		

*Note. (a) *** p < .001, ** p < .05; (b) test of nested models based on ANOVA results.*

4.4.4 Discussion

Overall, this final study revealed further evidence regarding the economic implications of consumers' certainty with the self-designed product. In essence, we found that consumers perceived certainty during the customization process is strongly related to the probability to finally buy the self-designed product. Together with our previous studies, we have shown that community interactions may have the potential not to increase but rather to decrease consumers' certainty during self-design processes and that this decision certainty is strongly related to subsequent economic decisions and therefore of a more general importance for companies running community based business models.

5. Discussion and Conclusion

5.1 Theoretical Implications

From a theoretical perspective, our studies revealed new insight that anonymous computer-mediated communication can reveal a direct influence on choice (study 1, hypothesis 1). This may generalize previous findings of classical social influence studies (see Wood (2000) for a review) and their implication for IS research. In particular, our manipulations of deviant feedback did not contain any fundamental argument why participants should consider the recommendation—the mere presence of a manipulated recommendation resulted in a considerable revision of choice and participants' initial preference. Furthermore, we found that these deviations led to systematic negative effects in terms of decreasing certainty (study 1, hypothesis 2 and replication in study 2). Thus, influencing individuals in at least a virtual context may result in less desirable effects in the long run. This raises general questions for online as well as offline social influence studies since the major dependent variable usually is the influence in terms of adoption of a certain product or service but not the post decisional analysis after this adoption. In general, we point out that the broader link of psychological constructs and theories may enhance our understanding of given theories and the relation to IS research. Developments of integrating normative constructs and the like in the eminent Technology Acceptance Model support this notion (e.g., Venkatesh et al. 2003). In this regard, we showed that individuals' self-esteem is a significant moderator of influence processes (study 1, hypothesis 3) that results in lower dependency on third-party opinions. The measurement of pre and post self-esteem with reference to external influence also revealed that the mere presence of a distant recommendation is able to reveal a direct negative influence on individuals' perception of self-worth (hypothesis 4). Thus, it must not necessarily be a direct offense or a negative feedback of other individuals—the presence of a strongly deviating recommendation may also contain the implicit information "what you did was not good enough". In addition, our results concerning the backfiring effects of positive affirmations may lead to less desired effects than previously intended (hypothesis 5), which at least calls for further assessment of applied affirmation strategies in a virtual context.

We also see a methodological implication. Previous research has considerably advanced our understanding of the qualitative relationships about why users participate in communities and how future participation is influenced by such interactions. However, on a methodological level it was noted (De Valck et al. 2009) that these links may not be exclusively reliable since survey-based methods are inherently based on measuring past behavior, or more precisely, the remembered past behavior. The use of controlled experiments may allow us to vary only the factors of theoretical interest while holding other influences as constant as possible. This allows us to establish the inherent causal link of directed hypotheses. Integrating modern tools with moderate programming and development effort enables us to run highly realistic experiments online. In essence, we see great potential for including more experimental research designs as soon as the general link between the theoretical entities of interest is established with previous qualitative or survey-based research.

5.2 Practical Implications

From a practical point of view, our results elucidated that interactions and recommendations of hardly known (or in our case explicitly manipulated) users may reveal a strong influence on individual decision behavior without the need to establish a strong social intimacy or shared goals between participants. Consider the case of a design contest or a start-up community where users can design a specific object of interest, show it within their personal profile, and may receive comments from other members. Now imagine that a user has posted her first personal design and is curious about reading what other members of the community might think and how they rank her self-designed object. We suspect that a rating with three out of five stars may motivate for a positive discussion but that it also can lead to feelings of rejection without knowing these other members personally and as a result may significantly influence this user's probability of posting new designs, engaging in discussions with other users, and in the long run her survival probability of staying within the community. We expect that these subtle mechanisms of social evaluation—without directly addressing someone personally—may considerably influence his or her behavior in the future. Since retaining and engaging new members are key dimensions in community practice, our results may guide practical strategies for a sort of "sentiment controlling". For example, companies could implement simple algorithms to measure users' activities and interaction (text based or ratings of designs, etc.) with other community members. Text-based comments could further be categorized with natural language-based text mining algorithms (e.g., positive, negative, neutral comments). In the second step, these variables could be regressed on members' inter-temporal participation rate and discussion activity. After the first few weeks, community owners could establish a threshold for reporting probably as negatively affected classified cases. This reporting system could build the basis for analyzing participation rates, discussion activity, etc. and past interactions between community members. An analysis of these data and a detailed reporting could help community owners to understand the qualitative influence of community interactions and their link to quantitative results, as possible reasons for lowered retention or participation rates.

5.3 Limitations and Future Research

To stimulate further research, we finally discuss the limitations of our results and derive new areas of research for future studies. First, we used a product category with high social visibility. Although it might be reasonable to extend our results to other socially visible categories (e.g., digital devices such as cell phones, cameras, and the like), it will be important to see if the same social influence processes can be virtually constructed for less socially visible domains such as financial products or products such as toothpaste, shampoo, or other fast-moving consumer goods.

Second, our research context was embedded only within a specific domain of a product customization community. It would be important to see if our results can be generalized for other research contexts. For example, we suspect that our results can also be applied to virtual collaborations of distant project teams and the analysis of how team effectiveness may change as a function of the type of reciprocal evaluations, the tone of commenting on each other, and the like. We could also imagine applications in learning-oriented communities and the way students comment on each other and in measuring the degree of learning success, community participation, and cooperation or helpfulness.

This leads us to a third aspect, the degree of social intimacy. In particular, it would be interesting to see if the effect of negative influence of deviating feedback on individuals' perception of self-worth and the increased choice deviation after receiving feedback (studies 1 and 2) is the same for members who already know each other. Although the latter assimilation effect may remain, it may follow that the first effect changes: individuals may hold more or less unconscious "friendship idiosyncrasies" that allow these individuals to deal with potential critiques.

From a fourth point of view, a more in-depth analysis of how users apply internal preference revision rules is needed and how these revisions evolve over time. Since we cannot rule out the possibility that consumers may have perceived the given recommendation in accordance with the feedback-prime of the first phase (e.g., answering questions about favorite color, fashion style, etc.), future research may focus more strongly on explaining the fundamental process of including exogenous information on internal preference formation and the underlying mental calculations of balancing both dimensions.

Finally, our study was conducted in a Western society. It would be interesting to see how our effects are moderated by cultural influences. In particular, it would be of major interest to analyze how individuals of more collective-oriented societies deal with and respond to these virtually constructed influence processes.

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Article III

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Increasing Brand Attractiveness and Sales Through Social Media Comments on Public Displays – Evidence from a Field Experiment in the Retail Industry

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Abstract

Retailers and brands are just starting to utilize online social media to support their businesses. Simultaneously, public displays are becoming ubiquitous in public places, raising the question about how these two technologies could be used together to attract new and existing customers as well as strengthen the relationship toward a focal brand. Accordingly, in a field experiment we displayed brand- and product-related comments from the social network Facebook as pervasive advertising in small-space retail stores, known as kiosks. From interviews conducted with real customers during the experiment and the corresponding analysis of sales data we could conclude three findings. Showing social media comments resulted in (1) customers perceiving brands as more innovative and attractive, (2) a measurable, positive effect on sales on both the brand and the product in question and (3) customers wanting to see the comments of others, but not their own, creating a give-and-take paradox for using public displays to show social media comments.

Keywords: Public Displays, Digital Signage, Pervasive Advertising, Social Media, Social Networks, Field Experiment, Mixed Methods, Retail Industry.

1. Introduction

Public displays – sometimes referred to as digital signage and "digital out-of-home media" (DOOH) – are becoming increasingly common thanks to technological advances and rapidly declining costs [11]. Accordingly, global spending on digital displays has shown strong growth, with sales of $6.47 billion in 2010, which is projected to expand by 16.9% in 2011. Not surprisingly, retailers are showing interest in business-relevant, consumer-facing applications which have the potential to change customers' interaction with retailers and their in-store experiences, giving public displays a prominent place in retail. However, despite these activities and the research interest in using public displays for advertising, it is estimated that DOOH advertising in general has not reached its full potential, largely because of the difficulty in measuring the return on investment [25]. To quantify the gap: while consumers on average spend 27% of their time exposed to outdoor advertising, this form of advertising in 2008 only comprised 5% of US media spending [13]. Thus, it is of a fundamental practical as well as theoretical importance to better understand underlying drivers of successful public display advertising strategies and their economic effects in terms of sales.

The field experiment described in this paper was conducted to better understand the effects of social media (SM)-based advertising on customers' attitudes and sales and as such, it was conducted in small-space retail stores (kiosks), where brand-related SM comments were shown on public displays. The newness of this pervasive advertising application prompted an explorative approach in which interviews were used to understand customer attitudes toward using SM comments on public displays, as well as a quantitative analysis of sales data to show how these attitudes might affect sales. The collaboration with the kiosks and the quantitative analysis of the field experiment are described as a case study in "Social Networks in Pervasive Advertising and Shopping" [7]. The present paper provides further depth by adding the analysis of customer interviews and the insights gained from understanding the customer's paradoxical attitudes towards SM and public displays.

Interviews conducted during the experiment provided insight into customer opinions and the corresponding analysis of sales data showed the effect on sales, resulting in three findings: (1) SM comments resulted in customers perceiving brands as more innovative and attractive. (2) The subsequent analysis of the sales data shows that displaying SM comments in stores have a measurable, positive effect on sales on both the brand and the product in question. In addition to these findings of practical importance, the paper advances the theoretical discussion by presenting evidence that (3) customers want to see the comments of others, but not their own, creating a give-and-take paradox for using public displays to show SM comments.

2. Related Work and Development of Hypotheses

Pervasive Advertising [17] enables the kind of serendipity common on TV, radio and print, with the added benefit of enabling new ad types [26] such as user-generated comments. Public displays in particular allows for a broad range of content from generic advertisements to ones that are responsive [18] or interactive [9, 16]. Since advertising in general is proven to increase shareholder value through increased sales [34], pervasive advertising research is being conducted to understand how to extend traditional advertising into the domain of pervasive computing. Based on previous findings which have shown the positive influence on the brand due to increased interactivity with the brand on Facebook and customer engagement [36], we expect a positive influence of using Facebook on public displays on a brand's perceived innovativeness.

> **H1:** The more positive a customer's attitude toward Facebook on public displays, the higher the brand's innovativeness will be perceived.

Furthermore, SM provides retailers access to a new type of word of mouth, which is a recognized force in retail [29,1,5] and has the appeal of precisely directing messages to a targeted audience. SM represents the natural technological platform for marketing based on a structured set of social relationships among admirers of a brand, i.e. a brand community [28]. Additionally, SM allows companies to listen to the opinions, wishes and complaints of their customers, as many consumers want constant connectivity, ideally in every facet of their lives [3]. Different consumer brands and retail stores are handling this opportunity and these challenges in different ways, some with spectacular success (e.g. Nutella allowing its 6.8M Fans to send each other virtual

Nutella gifts). As a result, we predict that brands will be perceived as more innovative when companies enable Facebook comments of friends on public displays.

> **H2:** The higher customers' attitude toward seeing Facebook comments of their friends on public displays, the higher the brand's perceived innovativeness.

Research based on prototypes applied in user studies has investigated embedding brands into the natural living environment and context of customers [33, 4], inferring a customer's activities for more targeted advertising [21], influencing their shopping behavior by means of persuasive strategies [27] etc. Public displays in retail stores can cater to this, thus satisfying both customer demand and taking advantage of sharing SM user comments in the retail environment to increase sales.

Past research considerably advanced our understanding of how and why consumers may engage in brand communities. However, research has also shown that privacy concerns are rising and may inhibit content production on the individual level [19], though users may nevertheless wish to consume the produced content on the social networking sites [12]. The moderating influence of the previously noted privacy concerns on the one hand and consumers tendency to enjoy seeing the content of others on the other hand, is expected to be positively related toward the brand's innovativeness. Thus, we predict:

> **H3a:** The higher customers' attitude toward Facebook on public displays and attitude toward seeing their own Facebook comments on public displays, the higher the brand's perceived innovativeness.

> **H3b:** The higher customers' attitude toward seeing Facebook on public displays and attitude toward seeing Facebook comments of their friends on public displays, the higher the brand's perceived innovativeness.

From the marketers' perspective, there are many strategic and operational benefits of cultivating brand communities. Brand-community participation results in a positive effect on consumers' attitude and attachment to the brand and the company [14]. From the consumers' perspective, users are interested in receiving brand announcements on their profile page, they feel they are a part of the brand communities they joined, accept friendship requests of the brand pages and value friends' opinion about a brand but at the same time feel concerned about the fact that companies may make use of this personal profile information [23].

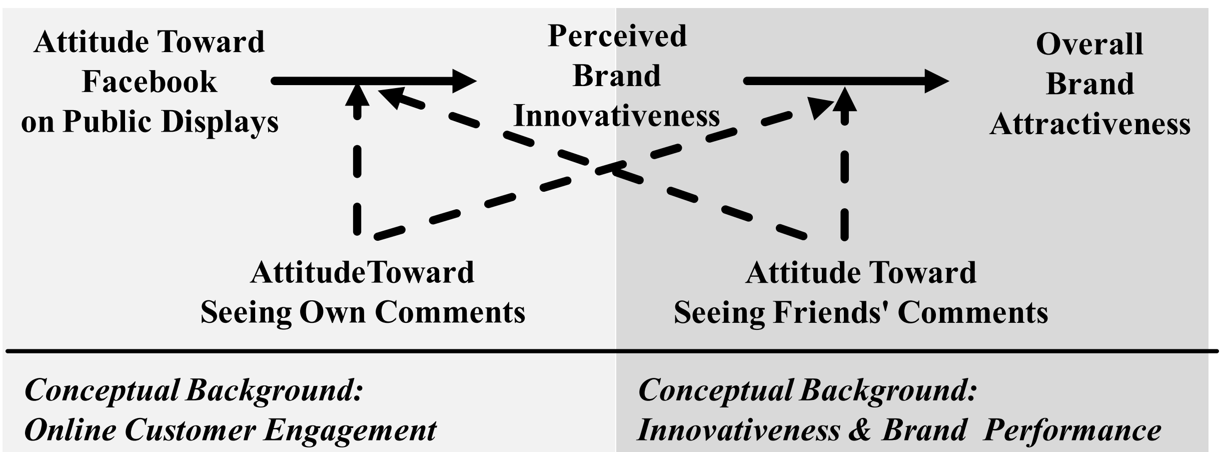
Thus, past research findings explain how pervasive technologies may increase a customer's perception of a brand as being highly innovative and balancing security issues at the same time. However, a test if this perception can also be transformed into an increase in global attractiveness and preference for the brand is still needed. Thus, we predict:

H4a: The higher customers' attitude toward Facebook on public displays and attitude toward seeing their own Facebook comments, the lower the brand's perceived attractiveness.

H4b: The higher a customers' attitude toward seeing Facebook comments of their friends and the higher the perceived innovativeness of the brand, the higher the brand's attractiveness.

Figure 1 summarizes our research model to explain the influence of attitudes towards SM on the perception of the brand's innovativeness and the mediating role of brand innovativeness on overall brand attractiveness.

Figure 1: Overview of Research Model



Past research also considerably advanced our understanding of how using SM for brand marketing enables companies to build and maintain close relationships with consumers [20]. However, it is far less understood how consumers' attitude toward SM sites may directly influence their perception of a company active on SM in general, nor is the influence on important business variables such as sales understood. The direct link between the previously introduced developments in the area of pervasive advertising and their effect on either attitude-oriented constructs – such as the perceived innovativeness or attractiveness of a company or directly measurable effects in terms of sales – is still missing [30]. Thus, we finally test if these attitude-oriented effects transform into an increase in sales. In particular, we predict that presenting company-specific content in contrast to a control condition of unrelated content will affect sales volume of the company positively. Furthermore, based on previous work in the area of consumer behavior [32] and our previous discussion on positive influence of customer engagement on innovativeness and brand attractiveness, we expect that (1) product-specific, in contrast to brand-specific information are associated with an increase in sales, as well as (2) SM comments, in contrast to traditional advertising, are associated with an increase in sales, due to the more personal nature of SM in comparison to traditional advertising. Finally, based on previous work in pervasive advertising [17], we predict a higher sales volume for sales locations at public transport meeting places because of the higher frequency of visitors making quick purchases.

H5: Using company-specific content on public displays leads to higher sales volume than random, company-unspecific content.

H6: Product-related content on public displays yields higher sales volume than brand-related content.

H7: SM comments on public displays yield higher sales volume than traditional advertising.

H8: Kiosks located in public transport areas and using public displays yield higher sales volumes than kiosks in standard shopping malls or airport kiosks using public displays.

3. Context of the Study

We conducted a field experiment in partnership with Valora Retail, which operates around 1000 small-space stores, known as kiosks. Sales show high frequency at small volumes of convenience products such as news, sweets, tobacco and lottery: together, kiosks serve 850'000 customers per day, who buy an average of 1.7 articles. These kiosks often function as meeting points and social hubs in the areas they are located in.

In an effort to increase sales and gain third-party advertising revenues, the retailer was conducting a public display experiment involving a total of 50 kiosk locations. Of those, 16 contained suitably large, 40" screens, which we could use for displaying SM comments (see Figure 2) in the field experiment. In addition, the team gained management support to use a kiosk private label brand, the "ok.-" line of products, which allowed for greater control than would have been possible with a national or global brand. Finally, a Facebook "Brand Page" was set up for the ok.- brand in March 2010, 9 weeks ahead of the field experiment. This brand page served as the source for the SM comments shown on the public display. As long as the comments did not violate the company policy (e.g. profanity, obscenities, etc.), we collected the comments by taking the three most recent posts at 8pm each day, regardless of whether the sentiment towards the brand was positive or negative (see also [23]).

Experimental Setup of Field Experiment. The field experiment covered 16 kiosks all over German-speaking Switzerland, located in airports, hubs of public transport, inside shopping centers and rural areas. To experimentally test the effects of SM comments on public displays, the content shown was systematically manipulated (see below).

These 16 kiosks were all equipped with a 40" screen, which featured a standardized layout determined by the retailer: an upper bar with time and date, a lower bar with news headlines and a side bar with infotainment such as weather and horoscopes. The design was part of the retailer's public display experiments and could not be changed for our field experiment. The experimental content was shown in stores for 5 weeks from 5th of May to the 8th of June 2010, so that every experimental condition was run for one week. The shown content was visible for 15 seconds within a two-minute loop. Figure 2 below shows an example of the public display placed within the kiosk environment.

Experimental Conditions. We systematically varied the content shown on the public displays. In particular, five different types of content were displayed on the public displays: in the first condition, we varied product- vs. brand-specific content. Secondly, we either presented traditional advertising vs. SM comments harvested the previous day from the ok.- Facebook fan page. Specifically, the three newest comments were collected every evening at 8 pm, including the author's first name and the initial of their last name. In addition, we had one control condition in which no manipulated content was shown. Thus, this resulted in the following conditions shown on the public display: (1) traditional advertisement of the ok,- brand, (2) traditional advertisement of the lead product (ok,- Energy Drink), (3) SM comments from the ok,- Facebook Brand page, (4) SM comments from ok,- Facebook Brand page (ok,- Energy Drink) and finally, (5) control condition (content unrelated to the ok,- brand).

Overall, this produced a final 2 (product vs. brand) × 2 (traditional advertising vs. social network comments) experimental design, and in addition, every kiosk was treated with a control condition where no experimental manipulations were shown. Every kiosk was randomly assigned to one of the five conditions lasting for one week each. Choosing which content to show in which location and choosing the timing was based on a completely randomized experimental design to minimize the impact of the different influences that come from the "natural" setting of this field study [16].

Figure 2: Social media comments for an energy drink on public display in a kiosk

4. Analysis I: Customer interviews

During the time of the field experiment, we conducted customer interviews in parallel to measuring sales data. While the cash register sales data was central to evaluating the economic impact of public display advertising on sales, the customer interviews were conducted to better understand the general attitude toward public display advertising, as well as the attitude toward SM and Facebook and the influence on general brand attractiveness. Thus, we present the customer interviews first, and will then provide additional evidence based on quantitative sales data in the next section, Analysis II.

4.1 Mixed Method Approach and Qualitative Interview Data

To explore customers' opinions regarding comments from SM on public displays, semi-structured guided interviews were conducted in kiosks showing SM comments on public displays. This method was chosen to account for the newness of the topic, hence the use of mostly open questions instead of a standardized questionnaire.

The interview questions were based on a questionnaire containing 20 questions which allowed yes / no answers with comments, except for two open questions noted below. Customers were first asked if they had noticed the display and whether they had seen the SM comments. In an open question, they were fist asked what they thought about showing SM comments on public displays in general. The next question asked if SM comments on public displays influenced their perception of the company (the comments received were coded for innovativeness of the company). Customers were also asked if this increased the attractiveness of the advertised brand, and the likelihood of purchasing products of this brand. Two questions aimed to determine whether customers would like to see their own comments displayed, and the comments of their friends, though this was hypothetical since no interviewee indicated that they recognized the people whose SM comments were being used on the public display. Since SM comments expressing both positive and negative attitudes towards the brand were shown during the field experiment, an open question asked customers for their opinion of seeing both types of comments. The final set of questions established demographic information, including Facebook usage.

A total of 131 interviews were conducted by approaching every customer in the kiosk after they had concluded a purchase. The answers were recorded on pre-printed questionnaires, which were later transcribed. The interviews were conducted at different times of the day, over the course of 10 days from 30 June to 9 July 2010, at 10 different and randomly chosen kiosk locations, in all of which SM comments were being shown on a public display.

4.2 Measurement and Coding Scheme

In a first step, the responses to the interview questions were entered and transcribed. Initial analyses revealed strong differences between participants' answers (e.g., strong rejection of SM vs. strong positive attitude toward SM comments on public displays). To capture these different nuances in customers' answers, for example comments about privacy, a five point Likert scale was set up to capture differences between comments and to analyze the general tendencies and relationships between variables. A five point Likert scale was used to measure (1) customers' general attitude toward displaying SM comments on public displays, (2) their attitude toward imagining seeing their own comments, (3) their attitude toward imagining seeing comments of others and (4) the perceived innovativeness of the brand and the brand's attractiveness. The scale was set up so that two independent coders assigned values between -2 for a strong negative attitude to +2 for a strong positive attitude with a neutral point at zero. To test the reliability of the scales, we conducted interrater reliability tests which are based on the degree of agreement among the two independent raters [31], supporting the quality and substantial degree of consensus with all values above .70 ($M_{Cohen's\_Kappa} = .814$, $M_{Intraclass\_Correlation} = .875$ (Min = .70, Max = .95)). Consumers' use of Facebook was measured by the number of Facebook use per day and consumers use of Facebook on mobile devices was measured by a binary variable (use vs. no use). Consumers' age was measured by discrete variable with six categories (see results section below in further detail). The SM comments themselves were not further analyzed for content, sentiment or attitude, though the interviews did capture customers' opinion of seeing both negative and positive comments.

4.3 Interview Results

Consumer Perceptions of Brand Innovativeness. In this first analysis, we were particularly interested in two questions: (1) consumers' perception of the brands innovativeness, as dependent on their attitude toward displaying Facebook comments on public displays in a retail store, and (2) their attitude toward imagining seeing their own comments, especially in comparison to their attitude toward imagining seeing the comments of others (e.g., friends and acquaintances) on public displays. In addition, four control variables were analyzed: consumers' age, being a fan of the ok,- brand's

Facebook brand site, intensity of Facebook use per day and use of Facebook Mobile. Table 1 summarizes our results based on a multivariate linear regression model.

Table 1: Results of Multivariate Linear Regression: Drivers to Explain Brand's Perceived Innovativeness

	Estimate	SE	t-Value	p-Value
Constant	.033	.134	.243	.808
Attitude Toward Facebook on PD (FBPD)	.174	.088	1.988*	.049
Attitude Seeing Friends' Comments (FC)	.109	.052	2.116*	.037
Attitude Seeing Own Comments (OC)	.039	.047	.832	.407
FBPD × FC	-.113	.084	-1.349	.180
FBPD × OC	.717	.199	3.6***	<.001
Facebook Mobile Use (MOB)	-.343	.158	-2.165*	.032
Facebook Use (in Hours / Day) (FB)	-.023	.022	-1.043	.299
MOB × FB	.063	.030	2.086*	.039
Age	.009	.030	.291	.771
Fan of Facebook Brand Site	.111	.242	.459	.647
F-Value	4.455***			
R^2	.28			

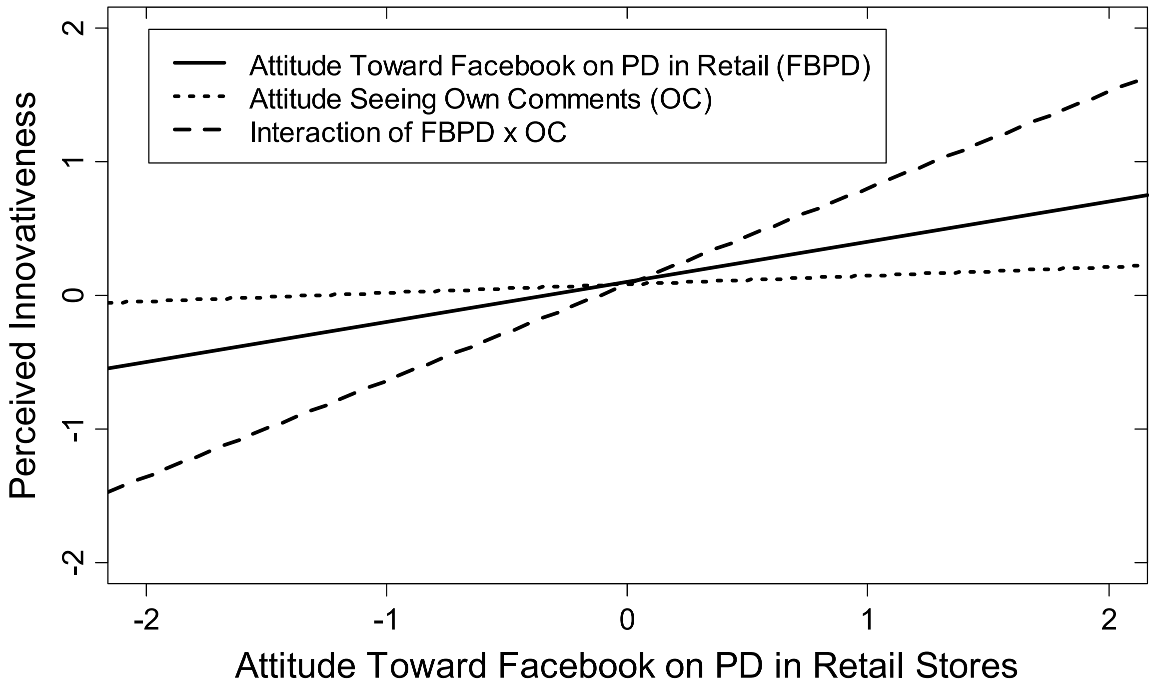
***p<.001, ** p<.01, *p<.05

As expected, we found a positive and significant influence of consumers' attitude toward displaying Facebook comments on public display (FBPD) in a retail store as well as consumers intention to see the comments of their friends (FC) on the perceived innovativeness of the company ($Beta_{FBPD}$ = .17, t(119)=1.988, *p* < .05; $Beta_{FC}$ = .11, t(119) = 2.116, *p* < .05), supporting hypotheses 1 and 2.

While consumers' attitude toward seeing own comments (OC) had no significant influence on perceived innovativeness alone ($Beta_{OC}$ = .04, t(119)=.832, *p* > .40), we found the predicted interaction between consumers' intention to see their own comments and the general attitude toward integrating Facebook on public displays ($Beta_{FBPD \times OC}$=.72, t(119)=3.600, *p* < .001), in support of hypothesis 3a and failing to support hypothesis 3b. Figure 3 illustrates the steeper regression slope compared to the simple main effect without controlling for consumers' intention to see one's own comments. Thus, we may already hypothesize that consumers' intention to see their own comments in contrast to seeing others may have different effects on subsequent evaluations of retail stores. This is analyzed in detail in the next section.

Finally, our analyses also revealed a significant interaction between consumers' use of Facebook Mobile (MOB) and intensity of Facebook use (FB) in a positive direction ($Beta_{MOB \times FB} = .06$, $t(119)=2.086$, $p < .05$). This result reveals that intense Facebook or Mobile applications use alone does not drive consumers' perception of a company's innovativeness, but rather the interaction of the two variables. Since the main effect of mobile use is significant but negative, this is an example of a disordinal interaction, i.e. mobile use needs to be interpreted in combination with the interaction of Facebook usage [2].

Figure 3: Illustration of interaction between attitude toward Facebook and attitude to see own comments on public displays on the company's perceived innovativeness



Overall, these initial results have shown that consumers build a strong link between a company's activity on Facebook brand sites and their intention to see their own comments on public displays on the perceived innovativeness of the brand. Interestingly, the influence of consumers' intention to see the comments of other users was not dependent on this interaction and may have more general implications than the dependencies to see one's own comments. However, (1) it is not clear how innovativeness is further related to the overall attractiveness of the focal brand and (2) how the tension between varying attitudes in seeing one's own compared to friends' comments is moderating this relationship. This detailed analysis will be part of the next section.

Influence on Overall Brand Attractiveness. As we have shown above, a consumer's attitude toward the integration of Facebook in a retail store is positively related to the perceived innovativeness of the company. Now we will expand our analyses by assessing the mediating role of innovativeness on brand attractiveness and the moderating role of consumers' attitude toward seeing own comments, as well as seeing friends' comments on public displays. To test our previous hypotheses, we conducted a moderated mediation analysis [24]. Thus, we use a mediation model which simultaneously estimates the influence of the two moderators (seeing own comments and seeing friends' comments). This model has the advantage over testing every specified hypothesis independently (e.g. with linear models or ANOVAs) by reducing the risk of an otherwise increasing type II error of statistical testing.

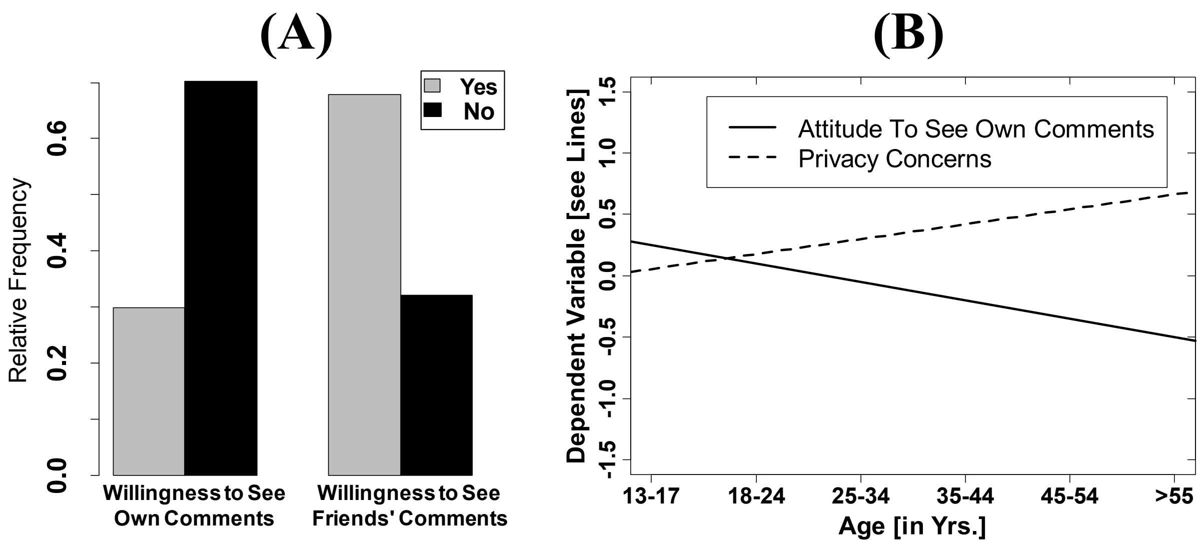
Since the effects in the mediator model remain equal compared to our previous analyses (interaction of attitude toward Facebook and attitude toward seeing own comments on perceived innovativeness of the brand ($Beta_{FBPD\times OC} = .58$, $t(125) = 3.616$, $p < .001$)), it will now be important to evaluate how a brand's attractiveness is affected.

Our analysis revealed a strong main effect of consumers' attitude toward integrating Facebook on public displays on overall attractiveness of the brand ($Beta_{FBPD} = .60$, $t(123) = 9.612$, $p < .001$), as well as a marginal positive effect of watching the comments of others ($Beta_{FC} = .07$, $t(123) = 1.891$, $p = .06$). While the latter influence of watching others significantly interacts with perceived innovativeness of the brand to increase the attractiveness of a focal brand ($Beta_{INNO\times FC} = .17$, $t(123) = 2.062$, $p < .05$), the influence of consumers' attitude toward seeing their own comments is as predicted, i.e. we find empirical support that although the possibility to see one's own comments was positively related to the brand's innovativeness (see results of the previous section), the main effect, as well as the interaction with the attitude toward integrating Facebook, is significantly negatively related to the attractiveness of a brand ($Beta_{FBPD\times OC} = -.25$, $t(123) = 1.988$, $p < .05$).

Thus, we find support for H4 (a and b) and our prediction that disclosing personal information in a public domain, such as public displays in a retail store, may have negative consequences regarding the overall attractiveness of a brand. In contrast, expecting to see others is strongly positively related to the attractiveness of the brand.

This contradiction is of major importance, since the inherent value of integrating SM into public displays is strongly dependent on the content of its users – however, if privacy concerns hold individuals back from adding content, while expecting others to do so, the irony and paradox of handling both competing preferences at the individual level may inhibit harnessing the full potential of pervasive advertising with public displays.

Figure 4: (A) proportion of consumers' willing to see their own vs. seeing comments of other users; (B) influence of consumers' age on privacy concerns and attitude to see own comments



To further explore this pattern of results, we analyzed the proportion of attitudes toward seeing one's own comments compared to seeing the comments of others by aggregating the data into either general positive or general negative attitude (see Figure 4) and found that both categories are highly statistically different ($\chi^2(1, N = 131) = 18.493$, $p < .001$). Moreover, additional analyses revealed that a strong demographic influence underlies this effect: the older consumers are, the less likely they are to want to see their own comments ($Beta_{Age} = -.15$, $t(129) = 3.909$, $p < .001$) and the higher their perception of privacy issues ($Beta_{Age} = .12$, $t(129) = 2.466$, $p < .05$).

Overall, we find that this inherent contradiction of handling consumer preferences to watch the SM content of others, while promoting content production at the individual level, may be one of the key challenges in the early phase of adoption and market diffusion of business models for SM on public displays.

Since the interviews clearly demonstrate that seeing others' SM comments on public displays has a positive effect on customers' overall perception of the attractiveness of the brand, the next question is to determine whether this translates to an increase in sales. For this, we analyzed the sales data gathered during the field experiment, as described above.

5. Analysis II: Sales Data

In the course of the field experiment, sales data was gathered for one of the company's new private label products: a type of energy drink. The data was analyzed to test hypotheses 5 to 8 and to determine the effects on sales of displaying SM comments of the company's new energy drink on public displays. This section details the field experiment conducted and results obtained. Complementary to the previous interview results regarding the more general customer attitudes toward the brand in relation to SM comments on public displays, this section will reveal particular evidence of how customers' buying behavior is influenced by these SM comments on public displays.

5.1 Methodology

5.1.1 Measurement

Sales data from each kiosk participating in the field experiment was transmitted to the retailers' central business intelligence system every night. From there, the retailer provided sales data for all the private label products. This allowed testing the effects of the experiment, which targeted the private label brand as a whole, and also the top-seller energy drink in particular. The data also covered the 5 months leading up to the experiment and provided insight into the development of sales prior to the field experiment. This historical data showed an emerging (rising) trend over time and was used to adjust the experiment data to eliminate this trend and only measure the experimental effect based on the conducted manipulations during the experimental phase.

5.1.2 Statistical model

In order to test our previous hypotheses and experimental conditions on sales, we applied a repeated measures linear mixed model (LMM) [22]. LMM's provide us with additional flexibility in model specification and allows us to account for inherent store-to-store variation and store heterogeneity within our field experiment as well as to model repeated effects on single stores over time. The respective error terms are assumed to be independent between different stores. Since all stores can be assumed to be randomly selected from a larger population, we specified the respective store as a random effect within our model, since we are not interested in specific effects of single stores but rather the hypothesized effects of our experimental manipulations. Additionally, since we have repeated measurements of single stores over time with high likelihood of correlation with each other (sales volume in one week is not independent of sales volume in the following week), we fitted several LMM's with varying covariance structure as a general procedure for model selection [15]. The general idea is to find the most parsimonious model specification that fits the correlated time series of sales data well. Therefore we started with a simple first-order autoregressive covariance structure (i.e., constant covariance between two measures and increasing the exponent of the covariance parameter with increased time steps) and expanded the model complexity systematically by applying an autoregressive moving-average, a toeplitz-based covariance matrix as well as a more complex unstructured covariance matrix (see [15] for detailed information on how these covariance matrices are specified). As a general procedure to choose the optimal model specification, we conducted likelihood-ratio (LR) tests between all nested model's [8]. Overall, the best fitting model was based on the unstructured covariance matrix and outweighs its higher number of to be estimated parameters (e.g., testing unconstrained (UN) vs. autoregressive (AR) model with a chi-square distributed LR test of $-2LL_{UN} = 842.25$ vs. $-2LL_{AR} = 890.66$, $\chi^2(1,13) = 48.41$, $p < .001$).

5.1.3 Experimental Results

To enable showing SM comments, companies must conduct substantial investments in public displays, as well as investments in organization and infrastructure. Thus, it is important to test for measurable effects in terms of sales volume and to quantify them. Table 2 summarizes the results of the LMM.

As predicted and in support of H5, showing particular and domain related content is positively associated with higher sales volume than unspecific random content: the experimental variation of the panel content yielded a significant positive main effect on sales in contrast to the control condition where only random and unspecific content was displayed ($F(1,91) = 4.12$, $p < .05$).

Furthermore, presenting specific product information in contrast to brand specific content yielded the expected main effect ($F(1,601) = 9.628$, $p < .01$), suggesting that product related content reveals stronger and more behavioral stimulating and compulsive effects than brand presentations, supporting H6.

Table 2: Parameter estimates of fixed effects from repeated measures LMM

	Estimate	SE	t-Value	p-Value
Experimental Condition[1]	24.5	12.06	2.03	.045
Brand Presentation[2]	-33.88	10.89	-3.11	.002
Traditional Advertising[3]	30.69	10.51	2.92	.004
Brand × Traditional Advertising	9.74	15.42	0.63	.528
Small Kiosk Type[4]	-40.43	8.63	-4.68	<.001
Sales Location[5] = Public Transport	26.62	8.21	3.24	<.001
Sales Location[5] = Local Retail	21.04	15.95	1.32	.187
Sales Location[5] = Shopping Mall	-1.57	17	-0.09	.926
Urban Area[6]	0.88	14.58	0.06	.952

1) Reference Category = Control Condition
2) Reference Category = Product Presentation
3) Reference Category = Facebook Messages
4) Reference Category = Large Kiosk Type
5) Reference Category = Airport Location
6) Reference Category = Non-Urban Area

Contrary to what we expected, we found a strong main effect of traditional advertising in contrast to SM comments ($F(1,357) = 28.641$, $p < .01$), thus failing to support H7. Building on previous work on information processing [32], this finding has to be reflected with regard to the general nature of a kiosk: consumers tend to selectively process given information at the point-of-sale due to consumers' time constraints. This means that retailers have to choose public display strategies that allow for very fast information processing with low cognitive involvement. Actively reading SM comments requires cognitive capacity as well as motivation to process textual stimuli, whereas easy to process visual cues of classical advertising are not dependent on this assumption and probably leading to this advantage of traditional advertising at the point of sale. Analyzing the control variables showed a significant effect for the respective sales area ($F(3,1411) = 5.267$, $p < .01$), and follow up contrasts revealed that this effect was attributed to the difference between airport and public transport locations ($M_{Airport – PublicTransport} = -26.62$, $SE = 8.21$, $p < .01$), supporting hypothesis 8. This suggests that retailers should strongly account for location specific effects that are dependent on the general target audience: while airport area stores are probably more frequented by international consumers that aren't familiar with a specific national brand, and possibly the language of the SM comments, this effect is reversed for locations with a high local awareness, like local public transport areas or shopping centers.

However, there was no significant effect for the degree of urbanity ($F(1,774) = .004$, n.s.) which underlines that the general effect of SM comments on public displays is not dependent on highly urban in contrast to non-urban areas. Note that although airport locations are usually in more urban areas, the general effect between urban and less urban places is less crucial − thus, retailers promoting national brands should focus more on installations on the right target location regarding the sales place, rather than distinguishing between urban and less urban places.

6. Discussion

Overall, the interviews conducted showed that customers attitude towards SM comments on public displays affect the perceived innovativeness of the brand, which in turn increases the overall brand attractiveness. Within these effects though lies the paradox of customers wanting to see comments written by friends on the one hand, while not wanting to see their own comments on the other. Regardless of this, displaying SM comments on public displays is positively associated with sales.

Perception of brand innovativeness and attractiveness. The interviews showed that customers perceive the brand to be innovative due to the SM comments shown on public displays. The perceived innovativeness held true in general for customers who liked seeing SM comments of other customers. In addition to the perception of innovativeness of the brand, customers responded that the SM comments on public displays increased the attractiveness of the brand being shown.

Effect on sales. The sales data analyzed clearly showed an increase in sales for both product-related SM comments as well as brand-related SM comments, though the product-related SM comments performed slightly better than general brand-related SM comments. However, for both, traditional advertising had a stronger effect still, probably due to the more cognitive as well as time consuming processing of the text-based SM messages in contrast to visual stimuli of classical advertising.

Furthermore, the analysis of our control variables revealed that the prevailing store circumstances are highly relevant for deriving effective retail strategies: while significant sales effects can be revealed by SM comments on public displays in local transportation areas, this effect is reversed for locations that are frequented by more international consumers.

Give-and-Take Paradox. Both qualitative and quantitative analyses point to the positive effects of using SM comments on public displays. However, while expecting to see SM comments of other customers is strongly positively related to the attractiveness of the focal brand, the data also provides support that customers feel that disclosing their own personal information on public displays in a retail store may have negative consequences on the overall attractiveness of a brand. Additionally, customers expressed concerns over privacy which need to be taken into account.

For the retailer, this paradox poses a problem in implementing a pervasive advertising strategy that relies on SM comments provided by customers. Since the medium is of major importance to advertisers, several advertisers have taken the intermediary step of repositioning their content to make it look similar to SM comments from customers in an effort to gain greater consumer acceptance [10]. However, this harbors the risk that the brand might be perceived as insincere, which violates WOM principles. Also, having the company generating content might be a time-consuming effort, since research suggests that due to the customized nature of using content from SM, the timeliness of the content is crucial in order to be meaningful, since delays might invalidate the context [6].

Implications. Our results significantly enrich our understanding of the efficiency as well as the effectiveness of pervasive advertising strategies that rely on SM comments on public displays. Our interviews and field experiment revealed new insights regarding the effectiveness of pervasive computing applications on public displays. Both data from the interviews, as well as the analysis of sales data showed that the integration of SM on public displays results in measureable effects in terms of brand awareness, willingness to purchase and ultimately on sales.

For the sales data, this was true especially for product-specific SM comments and less so for general brand-related comments. As traditional advertising content still trumped SM comments in this context of busy small-space shops selling low-involvement products, we conclude that the use of SM comments needs to be carefully evaluated. The context of customers ability to process textual stimuli in a shopping environment needs to be considered, possibly resulting in mixing traditional advertising with SM content.

Importantly, customers' paradoxical attitudes towards wanting to see the comments of others, but without showing their own needs to be taken into account, especially in view of the documented privacy concerns.

Limitations. Though we applied a very careful, fully randomized and balanced experimental design and to have controlled for external variability, ongoing local promotions, as well as external events, might have had relevant, spurious and hard to quantify effects for our respective kiosks. Ideally, the loop of our experimental variations should have been longer to be extensively processed by customers. In addition, we had a sample of 16 kiosks – highly unequal in terms of location, sales volume and so forth. Although our statistical model is ideal and state-of-the-art to account for such variability, future work could attempt to gain access to a larger sample size.

Most importantly the experimental setup of the public display at the point-of-sale and the basic screen layout were constrained by the retailer. Since we were working within an existing experiment of our industry partner, the recommended factors for placement of the public display, the content mix or format [16], could not be implemented. Any future experiment would need to attempt to control these factors.

7. Conclusion

Three main findings are presented that support the use of SM comments in pervasive advertising: (1) Showing SM comments on public displays increases customers' perception of the innovativeness and the attractiveness of the brand. (2) The effect on sales is positive – especially for SM comments relating to a specific product over a brand – though traditional advertising still has a stronger effect. Finally, (3) a give-and-take paradox exists in which customers' are influenced by whether they see SM comments from other people, which affects their opinions positively, versus a conflicted opinions when their own comments are shown. This, together with privacy concerns, poses a challenge for retailers.

Pervasive advertising researchers should consider developing systems that not only embrace customers fluent in the use of SM users but also to those who are not, in order to increase the positive perception of retail brands. Clearly, pervasive advertising research should focus more on local contexts and target groups, in order to more effectively exploit context-related SM content. The give-and-take paradox identified in this field experiment poses the challenge of designing a system that protects identities while still allowing friends to recognize each other on the screen.

Showing comments from SM on public displays improves the perception of innovativeness and the attractiveness of a brand, and – especially if they are product-related vs. brand-related – enhances sales. However, classical advertising still has general advantages due to a lower cognitive load regarding the route of information processing. This leads to our recommendation that a mix of the two advertising strategies should be based on careful analysis of the shopping environment and target group.

Future studies should assess how consumers' privacy concerns can be addressed effectively and examine additional forces that may also moderate the stated give-and-take paradox (e.g., different consumer segments with a stronger tendency to disclose personal information and explicitly gaining value by posting their own comments).

Furthermore, an extension on other product categories can help to better understand possible differences between high- vs. low-involvement products. Network based metrics could be applied to expand pervasive technologies toward identifying social hubs in the intersection of real- and online social networks. Finally, the effect on consumers' buying behavior due to semantic differences (e.g. negative vs. positive comments, specific vs. abstract, etc.) in SM comments could be analyzed.

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Article IV

Hildebrand, C. (in preparation for submission). Building, Testing, and Validating Agent-Based Simulation Models – Guidelines for the Rigorous Use of An Emerging Computational Research Method. *Information Systems Research*.

Building, Testing, and Validating Agent-Based Simulation Models – Guidelines for the Rigorous Use of An Emerging Computational Research Method

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Abstract

Agent-Based Simulation Models (ABMs) have been proven to be a useful and complimentary research method in a variety of recent applications. However, simultaneous debates emerged regarding how to rigorously build, test and validate ABMs. In this article, we review recent applications in major information systems journals and accentuate the current lack of general standards in building, analyzing, and validating ABMs. Based on these differences across and within journals, we provide a general set of guidelines for conducting rigorous ABM based research. The practical use of the proposed guidelines is illustrated by an example of viral marketing campaigns in social networks.

Keywords: Agent-Based Modeling, Reporting Guidelines, Simulation Study, Social Networks.

1. Introduction

Current information systems (IS) research is constituted by a rich variety of different research methodologies, paradigms, and theoretical foundations in diverse disciplines such as mathematics, economics, business, and organizational studies, among others (e.g., Benbasat and Weber 1996; Goles and Hirschheim 2000; Orlikowski and Baroudi 1991). This diversity is a reflection of the need to understand increasingly intertwined technological and social systems, and the way how technological artifacts and human behavior build in an inseparable conjunction (Agarwal et al. 2008; Kleinberg 2008). The complexity in studying such multi-level phenomena in IS research led to a recent increase in the use of Agent-Based Modeling (ABM) approaches (e.g., Bampo et al. 2008; Nan 2011; Rahmandad and Sterman 2008). This new methodology allows researchers to model and analyze complex and mathematically less tractable phenomena by analyzing the interactions of heterogeneous agents with distinct decision rules, goals, and attributes, to examine how local interactions affect the macro behavior of a system as a whole (Gilbert et al. 2007). Applying ABMs has been proven useful in a number of recent applications such as studying the diffusion of products and services in complex networks (Bampo et al. 2008; Weitzel and Konig 2006; Zaffar et al. 2011), the effectiveness of team collaborations (Adler et al. 2011; Cowan et al. 2007; Wang and Tadisina 2007), knowledge sharing (Wang et al. 2009), alliance formation of companies (Lin et al. 2007), or the general use of new technologies (Nan 2011).

Albeit the attractive properties of the ABM methodology to model adaptive agents (e.g., individuals, groups, organizations, markets, countries, etc.) and the rise of applications in IS research, there were also recent debates concerning the general validity of these models and the adequacy of their application (e.g., Windrum et al. 2007; Reiss 2011), as well as general critique about the diversity in reporting and documentation of ABM results (e.g., Richiardi et al. 2006). Unfortunately, this absence of commonly accepted standards in building, analyzing, and validating ABMs is negatively associated with the overall credibility of ABMs as a relatively new research method (Lorscheid et al. 2011; Nan 2011), and may hinder their acceptance among the IS research community.

To address these issues, we will review recent applications in major IS journals and support the current lack of general standards in building, analyzing, and validating ABMs. Based on these differences across and within journals, we will provide a general set of guidelines for conducting rigorous ABM based research. The proposed ABM guidelines are developed to clarify the appropriateness of the methodology when applying ABMs, allowing other researchers to build on already published models to assess their generalizability in future studies, as well as to provide general guidelines for assessing the rigorousness and credibility of developed models. The practical use of the proposed guidelines is illustrated by an example of viral marketing campaigns in social networks.

The remainder of the article is organized as follows: we will briefly review the historical and epistemological foundations of ABMs and the relationship to past modeling approaches, before evaluating recent applications in IS research. Based on these findings, we will provide a general framework of guidelines when and how to use ABMs, and apply these guidelines to an illustrative example for modeling viral marketing campaigns in social networks. Finally, implications for ABM researchers, the scientific community, graduate education, and quality control in IS publications are discussed.

2. Epistemology and Theoretical Background of the ABM Methodology

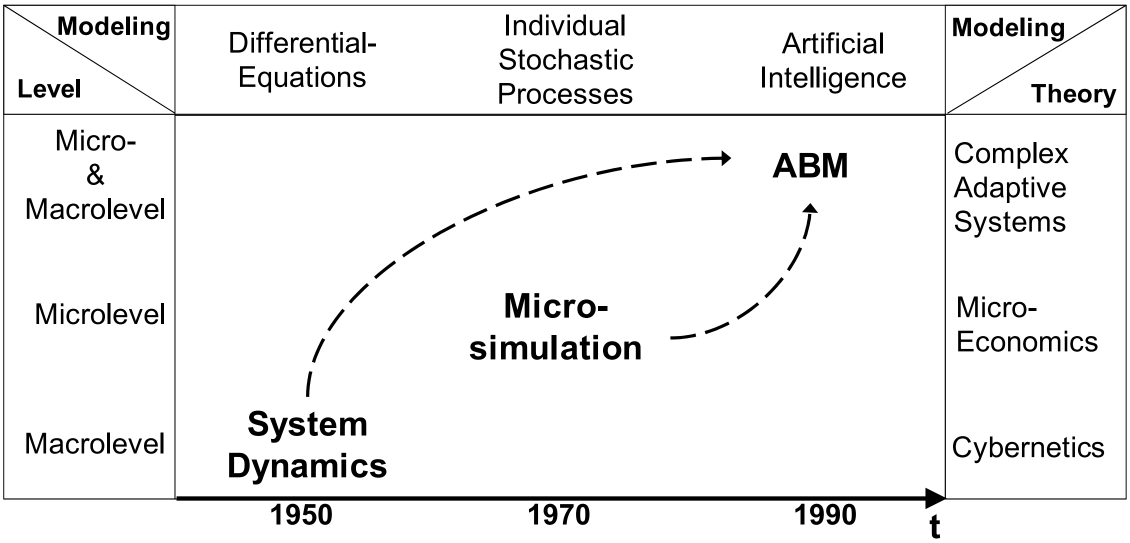
2.1 Complex Adaptive Systems and Computational Simulations

Developing ABMs is inherently related to so-called complex adaptive systems (Amaral and Uzzi 2007; Epstein 1999). Complex adaptive systems generally describe systems consisting of a number of autonomously interacting agents, resulting in emergent macro behavior which was not necessarily pre-specified by an axiomatic description (Holland and Miller 1991; Macy and Willer 2002; Sawyer 2003). The notion of adaptivity is the special case of intelligent agents who adapt their behavior to changes in their environment which can be based on interaction with other agents, receiving external information, or additional learning capabilities. Thus, modeling such processes is inherently based on previous developments in artificial intelligence, and developments toward distributed artificial intelligence during the last decades (Gilbert and Troitzsch 2005). As a result, building ABMs means to model a complex adaptive system of heterogeneous agents with (1) autonomous decision rules without a central instance of authority, (2) being able to react to external influence, (3) with learning capabilities, and (4) proactive behavior to actively change their actions over time (Macy and Willer 2002; Wooldridge and Jennings 1995). Thus, developing ABMs is strongly based on self-organization principles that create emergent behavior which was not explicitly pre-programmed into the model, but rather arises through interactions of its local entities (Gilbert et al. 2007).

To understand the epistemological assumptions of ABMs (see next section in detail), it is worth noting that ABMs evolved in distinction to other simulation techniques such as systems dynamics or stochastic microsimulations (Gilbert and Troitzsch 2005). While system dynamics models were essentially based on differential equations and used to predict complex system behavior purely on the macro level, such as population distributions or material flow in factories (e.g., Forrester 1958), stochastic microsimulations were built on the information from single entities directly (e.g., Lavington 1970; Orcutt 1990), and used to predict macro level observations from micro level information. However, modeling interactions on the individual level were not possible with each of these methodologies (Gilbert and Troitzsch 2005). A modeling approach able to cover such local interactions are cellular automata (e.g., Hegselmann and Flache 1998). Cellular automata are located on a lattice, and each cell's state is dependent on the state of its neighbors. Although cellular automata usually apply rather simple decision rules, it is possible to model complex system behavior that emerges by the local interactions of the cells. A famous example is Schelling's segregation model (1969), which showed that although individual agents may tolerate cultural diversity, their tendency to avoid being part of a minority resulted in segregation behavior by the system as a whole. Thus, Schelling showed how global segregation patterns evolve although individuals may not have explicit preferences for living in a segregated neighborhood.

Figure 1 illustrates the evolution of the ABM methodology and the different theoretical and methodological backgrounds compared to other computational simulation methods.

Figure 1: Synopsis and Development of Computational Simulation Approaches over Time



Thus, the development of the ABM methodology is inherently related to developments in other computational simulation techniques but in sharp contrast, ABMs are applicable to a wider variety of research problems due to their flexibility in model specification and use of micro- as well as macro-level data.

2.2 Epistemological and Ontological Differences Compared to Existing Research Paradigms and Methodologies

The use of ABMs has proven useful in a variety of different applications, and the previous section has shown that ABMs have distinct properties compared to other simulation methods. However, the question arises what implicit epistemological and ontological assumptions researchers make when applying ABMs. In the philosophy of science, ontology deals with the more philosophical question regarding the object of cognition, such as what exists, what reality is, and how reality is shaped by what exists (e.g., Henrickson and McKelvey 2002). In contrast, epistemology is related to the cognition of the object by the individual subject, and asks if and how knowledge about the object can be obtained (e.g., Becker and Niehaves 2007). These general criteria have led to different research paradigms with distinct assumptions (Goles and Hirschheim 2000; Weber 2004). Without loss of generalization, the two most prominent research paradigms which have been distinguished during the last decades are positivism and interpretativism (Chen and Hirschheim 2004; Orlikowski and

Baroudi 1991). The major differences between these paradigms are that positivists build their research paradigm around the ontological assumption that reality exists objectively and independent of human beings, whereas interpretativists stress the subjectivity and subjective construction of reality. Epistemologically, positivists deductively test hypotheses and aim to gain generalizable knowledge through falsification or non-falsification of hypotheses, and to explain and predict existing phenomena (Becker and Niehaves 2007). In contrast, interpretativists rather rely on a non-deterministic point of view in which understanding single cases, without generalization through a large sample size, is at the core of the research paradigm. Thus, while new knowledge in the positivist paradigm is gained through applying quantitative research methods and the results of large scale statistical analyses, knowledge in the interpretative paradigm is gained through the use of more qualitative research methods by analyzing single cases, small field studies, or interviews.

The question arises how do ABMs fit into these current paradigms? In essence, neither paradigm fully matches the unique properties of ABMs. In a previous attempt to distinguish these properties and characteristics of ABMs, Epstein (1999) embedded ABMs into the broader context of a more generative (computational) social science. Herein, he notes that “from an epistemological standpoint, generative social science, while empirical […], is not inductive, [whereas] generative implies deductive” (p. 43-44). Thus, Epstein proposed that ABMs should be build deductively on already existing theory to model a particular phenomenon, and also, to test competing theories by using ABMs (see section 3 in further detail). However, Epstein’s arguments do not imply that ABMs could only be applied to the extreme of a positivist, deductive research paradigm. In fact, ABMs where already used in case studies and qualitative research (e.g., Habib 2008; Moss 2008). Thus, empirical findings from previous research can be used to calibrate and to validate ABMs, but at the same time, ABMs can also be used to derive new propositions from qualitative research studies, providing a more dynamic perspective of the phenomenon. As Nan (2011) notes, ABM is “positioned at the “sweet spot” between […] interpretative case analysis and variance-based analysis” (p. 528).

In essence, applying ABMs can be seen as the analogous tip of the iceberg that is most visible when applying a particular research method. However, below the surface and mostly unseen, epistemological and ontological perspectives strongly shape researchers assumptions when applying any research method (Becker and Niehaves

2007; Henrickson and McKelvey 2002). As a result, although ABMs offer a unique methodological approach, encouraging a rapprochement of the traditional either positivist or interpretativist paradigm, new challenges arise when researchers from diverse backgrounds and different ontological and epistemological assumptions apply this new methodology.

2.3 Current Methodological Issues

Although the application of ABMs in IS has gained considerable interest and importance, four major methodological issues have been discussed recently (e.g., Grimm et al. 2010; Lorscheid et al. 2011; Reiss 2011).

The first issue reflects the theoretical basis when developing ABMs. Although previous research stressed the importance of model specification based on a strong theoretical basis (Epstein 1999), it has been noted that a solid theoretical foundation of ABMs is missing and conceptual flaws are existent (Railsback 2001). In addition, Jager and Janssen (2003) underlined the importance of more strongly develop ABMs based on previous research in behavioral and social science when programming agent behavior and learning capabilities.

The second issue is related to the standardized reporting of simulation results (Axelrod 1997; Lorscheid et al. 2011). While clear guidelines exist for reporting standard statistical results in empirical research, there is no such thing for ABMs (Richiardi et al. 2006). For example, when running an ABM, it is important to assess the sensitivity of the model for a broad range of model parameters. However, such parameter sweeping and sensitivity analyses are either not reported in many simulation studies, or relevant information about the distribution of parameter values is missing (Grimm et al. 2010; Reiss 2011; Richiardi et al. 2006).

Thirdly, it has been noted that ABMs have black-box qualities since model implementations are not well documented (Lorscheid et al. 2011; Railsback 2001). In particular, the key issue is to present in sufficient detail how the theoretical or conceptual model relates to the mathematical model, and how the mathematical model in turn relates to the computational model (Zeigler 1972). Only a concise model development with clear presentation of the underlying formal model allows other researchers to understand and evaluate subsequent model results (Bankes 2002). As a result, there have been recent attempts to strictly mathematize the process of model building by formal language (Zeigler et al. 2000). In essence, central model variables need to be presented in a more formal way to ensure mutual understanding.

The fourth critique is related to the validation of ABMs and has been discussed widely in recent years. In particular, although many models are briefly evaluated in terms of their face validity on the conceptual level, externally validated models are relatively seldom (Windrum et al. 2007), and the type of proposed validation ranges from interpretative assessment of historical events (Moss 2008) to a strictly statistical validation of models (Kleijnen 1995; Windrum et al. 2007).

Thus, recent debates on the appropriate use of ABMs highlight the unfortunate diversity of (A) not considered but existent theories as a conceptual basis for ABMs, (B) the computational implementation of conceptual models, (C) seldom used experimental procedures to test model parameters for a variety of cases, and (D) hardly validated ABMs.

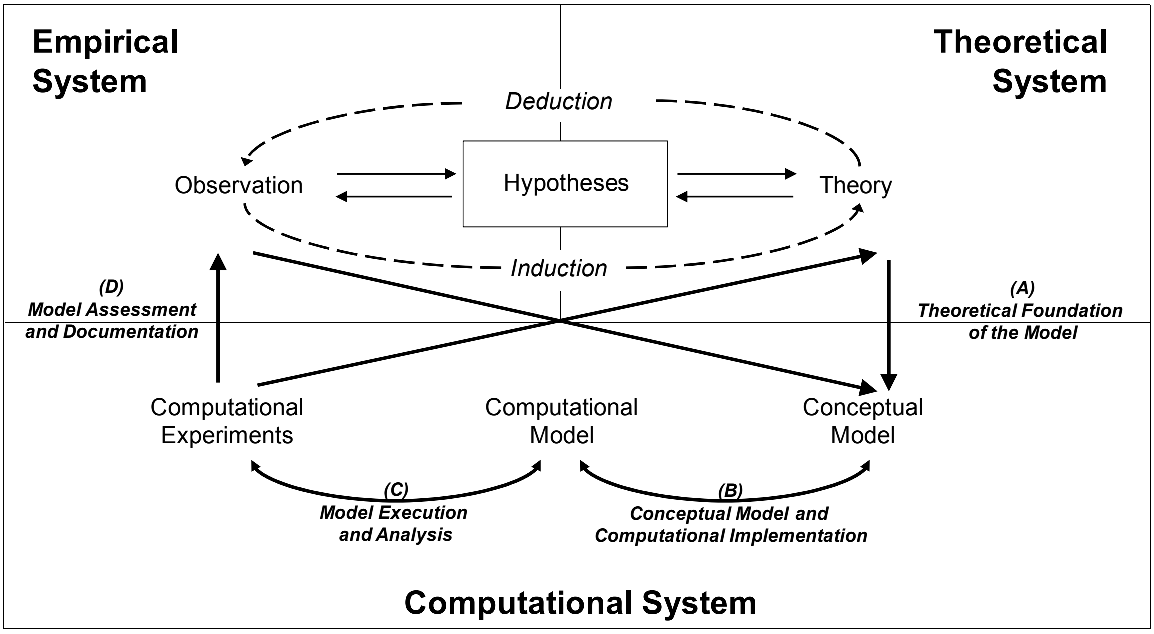
3. Analysis of Recent Applications in IS Research

3.1 Overview and Procedure of Analysis

To test if these previously noted issues concerning (A) the theoretical foundation of ABMs, (B) their computational implementation, (C) the design of computational experiments, and (D) their assessment and documentation are also existent in IS research, we analyzed recent articles published between 2004 and 2011 in leading IS journals (Information Systems Research (ISR), MIS Quarterly (MISQ), Management Science (MS), Journal of Information Technology (JIT), Information & Management (IM), Decision Support Systems (DSS), and ICIS Proceedings (ICIS)). Journal databases were searched manually using the keywords «agent-based model», «agent-based simulation», «computational simulation», «complex systems model», and «complex systems simulation». We only included manuscripts that explicitly developed an ABM, and excluded manuscripts that draw qualitative inferences on previously published models (e.g., Curşeu 2006). We also excluded computational simulation models such as NK models (e.g., Rivkin and Siggelkow 2007), or cellular automata (e.g., Hegselmann and Flache 1998). However, we carefully reviewed these articles for differences in terms of model building and reporting. While these models are slightly different, methodologically and conceptually, our analysis of recent ABM publications and our suggested guidelines may nevertheless generalize to related computational simulation methodologies. The final sample included a collection of 23 articles published within the last eight years (see Table A1 in the appendix). Note that more than 82% of analyzed manuscripts were published since 2007 ($M = 2008$, $SD = 2$), supporting the increasing interest in this rather new computational research method.

All articles were analyzed with respect to the four previously noted issues in terms of (A) theoretical foundation of the model, (B) the link between the conceptual and computational model, (C) the conducted computational experiments and analyses, and (D) if and how ABMs were assessed by means of their validity as well as their documentation. Figure 2 illustrates how these dimensions relate to each other from a process perspective, and how the empirical, theoretical, and computational systems are linked to each other on a conceptual level. In particular, the first step is to derive a conceptual model based on a set of core constructs or theories. Although this step is assumed to be driven theoretically, empirical phenomena may also influence model development in absence of existing theoretical explanations. The second step is to conduct the computational implementation of the conceptual model. Thirdly, after completing sufficient verification tests of the model, the ABM is tested for a variety of parameter combinations by conducting computational experiments. Finally, the model is assessed and evaluated based on empirical findings and theory.

Figure 2: Relationship between Empirical, Theoretical and Computational Systems when Building, Analyzing, and Evaluating ABMs

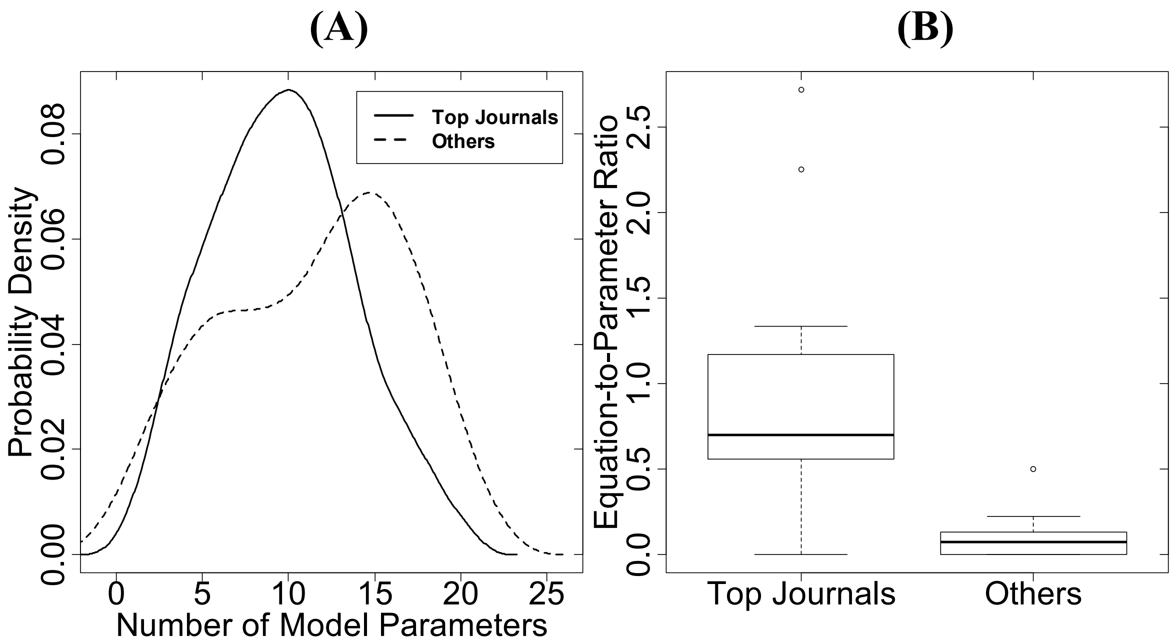


3.2 Analysis of Recent ABM Applications

Our analyses of the theoretical foundation of recently published ABMs (section A in Figure 2 above) revealed that only 74% of all manuscripts explicitly discussed the theoretical background of the model and only 52% discussed the general applicability of the ABM methodology to model the particular phenomenon. These results generalize across journals, since we found no statistical difference between top ranked and lower ranked journals (we defined top ranked journals as $\mathrm{TopR} := \mathrm{m} \in \{\mathrm{ISR}, \mathrm{MISQ}, \mathrm{MS}\}$ for each manuscript m; and lower ranked journals as $\mathrm{LowerR} := \mathrm{m} \notin \{\mathrm{TopR}\}$; $\chi^2_{\mathrm{Theory}}(1, N = 23) = 1.155$, $p > .28$; $\chi^2_{\mathrm{Applicability}}(1, N = 23) = 2.112$, $p > .14$), and we found only a marginal positive association within manuscripts that discussed both the theoretical background and the applicability of the ABM methodology ($\chi^2_{\mathrm{McNemar}}(1, N = 23) = 2.778$, $p = .095$, Odds $\mathrm{Ratio}_{\mathrm{Theory\_Applicability}} = 1.05$; $\varphi_{\mathrm{Theory\_Applicability}} = .22$). We also measured the ratio of the number of pages related to the theoretical background relative to the overall manuscript length and found no statistical difference between journals ($M_{\mathrm{LowerR}} = .134$ vs. $M_{\mathrm{TopR}} = .139$, $t(22) = .140$, $p > .88$). Thus, we revealed that only every third out of four manuscripts reported the theoretical background of the model, and only every second out of four manuscripts discussed why ABM is the appropriate methodology—these results were obtained independent of the journals' quality.

Furthermore, regarding the link between the conceptual model and the computational model (section B in Figure 2 above), we found that while 60% provide an explicit mathematical model of the ABM, only 8% provide real or pseudo code to assess the model implementation ($\chi^2_{McNemar}$ (1, N = 23) = 10.286, $p < .05$). In addition, a between group analysis revealed strong differences between manuscripts, such that manuscripts in higher ranked journals always reported the underlying mathematical model, while manuscripts in the lower ranked journals only reported the mathematical model in 25% of all cases (χ^2 (1, N = 23) = 13.554, $p < .001$). On a more detailed level, we counted the number of model parameters of every ABM and computed the ratio of mathematical equations relative to the number of model parameters for each manuscript. We found that although the mean number of model parameters and their variance is similar across journals ($M_{LowerR} = 11.4$ vs. $M_{TopR} = 9.6$, $t(22) = .945$, $p > .35$), strong differences in mathematical formalism emerged: while on average every single model parameter is presented mathematically for manuscripts in top ranked journals, this ratio reduces to only one out of 10 parameters for lower ranked journals ($M_{LowerR} = .10$ vs. $M_{TopR} = .99$, $t(22) = 3.531$, $p < .05$), despite the larger variance of the equation-to-parameter ratio within the group of top ranked journals ($F(11,10) = .031$, $p < .001$; see Figure 3).

Figure 3: Similarities and Differences among Journals regarding Number of Model Parameters (A) and Equation-to-Parameter Ratio (B)

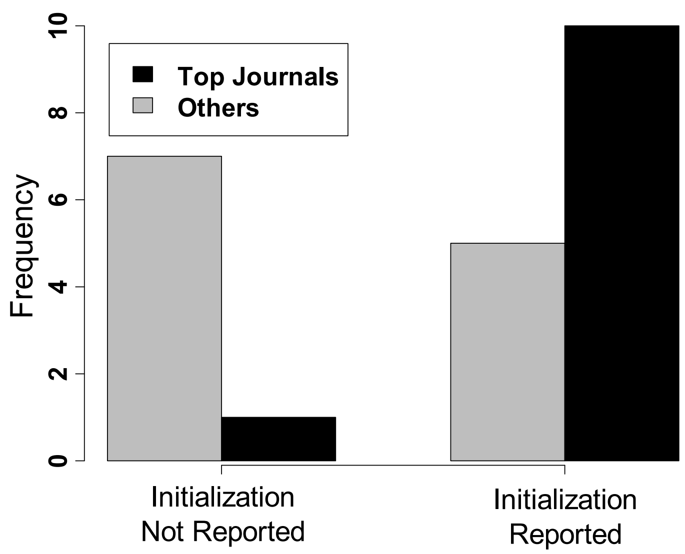


We also used the equation-to-parameter ratio within a linear regression model to predict changes in the ratio of the length of the theoretical background section relative to the length of the model development section (both measured in page units). Our analyses revealed that increasing the equation-to-parameter ratio led to a significant decrease of the theoretical background section ($Beta_{equation\text{-}to\text{-}parameter\_ratio} = -.24$, $t(21) = 3.313$, $p < .05$; $R^2 = .34$), thus, the increasing degree of formalism is associated with a significant decrease in the theoretical development part of manuscripts.

To evaluate ABMs appropriately, reporting the input values of the parameters and their distribution is necessary (Grimm et al. 2010). However, we found that although input values are provided in 91% of all manuscripts, their distribution is only reported in 8% ($\chi^2_{McNemar}$ (1, N = 23) = 11.267, $p < .001$). These differences may hold generally since we found no differences across journals ($\chi^2_{InputValues}$ (1, N = 23) = 2.008, $p > .15$; $\chi^2_{Distributions}$ (1, N = 23) = 1.058, $p > .30$). Fortunately, and as generally suggested in software engineering and model building (e.g., Grimm et al. 2010; Zeigler et al. 2000), we found empirical support based on a logistic regression model that the probability of using flowcharts for model presentation increased with the number of model parameters ($Beta_{NumberParameters} = .26$, $z(21) = 2.018$, $p < .05$). Thus, although models may increase in complexity due to the increased number of parameters, manuscripts with flowcharts may help readers in following the general procedure of the ABM.

Our analysis of the model execution part and computational experiments (see section C in Figure 2 above) revealed that only 65% of manuscripts reported how the model was initialized. However, variation in reporting of model initializations was strongly dependent on the group of journals. While 91% of top ranked journals reported how the model was initialized, this was true for only 42% of the lower ranked journals (χ^2 (1, N = 23) = 6.135, $p < .05$; see Figure 4). As a result, and supporting the previous notion on more formal driven model development in top ranked journals, the proportion of model initialization and mathematical model presentation was strongly associated with each other (Odds $\text{Ratio}_{\text{Initialization\_MathModel}} = 45.5$; $\varphi_{\text{Initialization\_MathModel}} = .72$).

Figure 4: Differences in Reporting of Model Initialization among Journals



Furthermore, we found that only 47% of the analyzed manuscripts used experimental designs for conducting systematic computational simulations, and only 56% used statistical procedures to analyze the generated data afterwards (e.g., to analyze main affects and interactions among model parameters, etc.). This variation among the design of computational experiments and analysis was independent of the journals' quality ($\chi^2_{\text{ExperimentalDesign}}$ (1, N = 23) = 1.110, $p > .29$; $\chi^2_{\text{StatisticalAnalysis}}$ (1, N = 23) = 1.051, $p > .31$), but the use of experimental designs was strongly associated with subsequent statistical analysis of the generated data (Odds $\text{Ratio}_{\text{Experiments\_Statistics}} = 29.99$; $\varphi_{\text{Experiments\_Statistics}} = .66$).

Finally, we also assessed the variation in model assessment and documentation (see section D in Figure 2 above). Although recent work has noted the importance of model validation (e.g., Windrum et al. 2007), we found that while 95% discussed the models' more general face validity (e.g., conceptual assessment of how well the model reflects what was intended to be modeled), only 69.5% actually discussed how well the model captures the real world properties based on empirical findings, and only 30% validated their input parameters based on empirical data. In addition, we found a general difference between journals such that 91% of all top ranked journals assessed the model based on observable real world properties, while this was true in only 50% of lower ranked journals (χ^2 (1, N = 23) = 4.537, $p < .05$). However, parameter validation based on empirical data was not attributable to differences in journal quality (χ^2 (1, N = 23) = 2.246, $p > .13$). Finally, only 8% of manuscripts offered access to the ABM based on an online repository, journal archive, or on their own webpage.

3.3 Discussion of Recent ABM Applications

Our analyses of recent ABMs revealed considerable differences in models' (A) theoretical foundation, (B) computational implementation of the conceptual model, (C) systematic design and analysis of computational ABM experiments, and (D) assessment in terms of validation as well as model documentation. In sum, we found both more general effects that were independent of the journals quality, but also differences that were strongly associated with the journals' ranking.

On the one hand, our analyses revealed a generally low level of theory driven development of ABMs, and only low levels of model testing based on systematic experimental designs. On the other hand, we found that differences concerning mathematical and algorithmic presentation of ABMs as well as validation issues were strongly associated with the journals' quality. In particular, we found that since top ranked journals are more strongly quantitatively driven, published manuscripts were well specified and documented mathematically, enabling future replication studies as well as model extensions.

In essence, these differences in model development, analysis and validation are severe and could impede ABMs full acceptance among researchers in the future (Richiardi et al. 2006). Imagine publications on the technology acceptance model (Davis 1989) during the last 20 years that would have been based exclusively on self-developed measures on the core constructs such as perceived usefulness and behavioral intentions in every single study. Developments toward a more generalized view of the technology acceptance model (Venkatesh et al. 2003) would have hardly been possible, if every study and every group of researchers would have developed their own measures and methods of analysis, completely unrelated to all previous work.

Thus, although past ABM publications were valuable and important in their contribution to the field on a substantive level, our aim is to move forward to develop clear guidelines for the ABM methodology to reduce the variation in building, analyzing, and evaluating ABMs.

4. A Framework of ABM Guidelines

To address the differences in building, analyzing, and validating ABMs, we introduce a set of guidelines for conducting appropriate ABM based research (see Table 1). As we pointed out, missing guidelines on how to apply ABMs rigorously impedes the diffusion and acceptance of this new methodology. Thus, we derive our following guidelines from recent discussions on specialized topics such as experimental designs for computational simulations, model verification, model validation, and documentation of ABMs (Grimm et al. 2010; Lorscheid et al. 2011; North and Macal 2007; Richiardi et al. 2006). According to our previous overview of recent applications and procedural perspective (Figure 2 above), our guidelines will address all four areas concerning the (A) theoretical foundation of an ABM, (B) development of the core model, (C) model execution and analysis, and (D) model assessment and documentation of the ABM (Table 1 provides an overview of our proposed guidelines).

Similarly to Hevner et al. (2004), we position our work as methodological guidelines to increase the rigorousness of new methods in IS research, in our case regarding the appropriate use of ABMs. Finally, these guidelines were not developed to highlight the flaws of previous work, but rather to establish a set of guidelines to promote the appropriate use of ABMs as a new and powerful research method in the future.

Table 1: Guidelines for Rigorous ABM Research

Guideline	Description	Purpose
Theoretical Foundation of the Model		
1. Purpose of the Model and Hypotheses	State the models' intention and research question explicitly.	Helps to (1) assess the general aim of the model, and (2) to develop the subsequent guidelines deductively.
2. Applicability of ABM Methodology	Discuss why ABM is the adequate methodology based on complexity theory (e.g., emergent and non-linear real world properties, adaptive agent behavior, temporal dynamics etc.).	Clarifies if ABM is the appropriate method based on the research question and to be modeled phenomenon.
3. Theoretical Foundation and Related Work	Provide information to which extent the model is related to already existing theories and previously published models.	Enables extension and refinement of existing theories and prevents atheoretical work.
Conceptual Model and Computational Implementation		
4. Model Entities	State the models' micro and macro entities explicitly. Decription of model entities should be at least verbally and mathematically. Provide algorithmic implementation if necessary.	Assures appropriate definition of the model based on theoretical constructs and transformation into formal language.
4.1 Micro Level: Agent Behavior	Provide information regarding agents' behavior and properties (e.g., adaptation, learning, different classes of agents, etc.)	Enables definition of micro level characteristics based on previous research (e.g., results of behavioral science).
4.2 Macro Level: Environment and Typology	Provide information regarding the system as a whole (e.g., spatial distribution, network topology, clustering of subgroups, size of population, etc.)	Enables definition of macro level characteristics based on previous research (e.g., results of network science).
5. Model Input	Present a list of all input parameters of the model, including their range of possible values and statistical distributions (e.g., normally distributed, uniform distributed, etc.)	Allows to draw inferences of how reasonable the range of parameters are according to the formal model as well as appropriateness of statistical distributions.
6. Model Output	Declare the measured model output explicitly which is used for later analyses.	Allows to understand the models' output in terms of the to be answered research question.
7. Procedural Overview of the Model	Provide a flowchart regarding the finally implemented model (especially for complex models with a large number of parameters).	Helps to connect the algorithmic and computational implementation toward the step-by-step process within a simulation run or sequence of runs.
Model Execution and Analysis		
8. Model Initialization	Assessment of how the model is created at the beginning of a simulation run (e.g., starting values of the model, stochasticity of model initialization (e.g., random seeds)).	Enables replication of published results.
9. Model Verification	Test if model and algorithms are implemented as intended according to the conceptual model.	Assures that computational implementation was conducted adequately.
10. Computational Experiments	Conduct simulation experiments for a reasonable range of parameter values and provide information of how experiments were conducted (e.g., factorial design of the	Enables identification of interaction effects between parameters (i.e., the dependency of a parameters' influence based on the values of other parameters).
Modell Assessment and Documentation		
11. Model Validation	Assessment of how well the model reflects the phenomenon and real world characteristics (e.g., by assessing models' "face validity" (extent to which theoretical concepts are modeled adequately), "external empirical validity" (extent to which observable real world properties are captured), "convergent validity" (extent to which model results deviate from previous models)).	Provides necessary information to evaluate the credibility of the model and its real world applicability.
12. Model Documentation and Archiving	(Pseudo) Model code and / or executable program should be provided in technical appendix or online repository (e.g., of the journal, www.openabm.com, etc.).	Enables theoretical extensions for future studies (see guidelines 1 to 3).

4.1 Theoretical Foundation of the Model

(1) Purpose of the Model and Hypotheses: First, manuscripts may provide clear arguments regarding the general purpose of the model and to lay out the underlying research question which is to be answered. As we have shown, all analyzed models in the previous section explicitly stated their purpose (i.e., what kind of problem the model is going to address or solve). This initial clarification helps readers in assessing the general aim of the model and is a necessary precondition for all following guidelines, for instance, to derive the theoretical foundations deductively according to the general aim of the model. As a result, previous work that might be or might not be

based on computational models as well as ABMs in particular, can be specifically related to the contribution of the promoted work.

(2) Applicability of the ABM Methodology: Secondly, authors should present a brief discussion as to why ABMs are the appropriate research method to study the respective phenomenon. Thus, authors may briefly lay out which elements of the real world phenomenon are assumed to fulfill the necessary preconditions of an ABM such as temporal dynamics, adaptivity of agent behavior over time, emergent or non-linear system behavior, amongst others, to clarify why ABM is a well suited research method to answer the particular research question. For example, according to Bonabeau (2002) as well as to North and Macal (2007), ABMs are well suited when (1) the phenomenon to be modeled consists of a set of heterogeneous agents (e.g., individuals, teams, organizations, markets with different preferences, decision rules), (2) the interaction between these agents is complex and non-deterministic, (3) agents' behavior is adaptive to particular events within the process of interactions (e.g., agents can learn and change their subsequent behavior), (4) the development of the system may change due to the dynamic process of interaction and is not inherently predefined as an input to the model, and (5) spatial aspects may influence agents' behaviors and the outcome of the interactions (e.g., based on the topology such as networks—see guideline 4 in further detail). Providing a short description why ABMs are the appropriate methodology to answer the underlying research question also clarifies how the developed ABM complements or reveals new theoretical as well as practical insight compared to previously used research methods.

(3) Theoretical Foundation and Related Work: After having laid out why ABM is the appropriate methodology, authors may provide an overview of how the model is related to already existing theories and previously published models. Since many theories are built around previous findings in the area of behavioral science with numerous replications in controlled laboratory studies, a strong advantage of ABMs in-built capabilities can be used to derive models which explicitly reflect these previous findings. But rather than study the effect of a treatment on a participant or group of participants, it is possible to simulate the dynamics of interactions among participants, i.e. agents. Furthermore, models that may consist of a new mathematical implementation of a given theory that is not related to empirical parameterization, while previous research already converged to an empirically tested implementation,

should provide more information than the model itself (e.g., special cases or propositions, where the established theory or past models may not hold).

This third step completes the section on the theoretical foundation of the model and clarifies how the current work differs from previous work, and how it adds value to the previous stream of research.

4.2 Conceptual Model and Computational Implementation

(4) Model Entities: First, when implementing the computational model based on the previously derived conceptual model, a brief overview of the model should be given with a description in verbal and mathematical terms. Implementation of the code or pseudo code can be provided in a technical appendix if necessary (see guideline 12 on documentation). However, although a verbal description of the model is provided in most studies, its algorithmic and formal description is not commonly reported, as we have shown in the previous section. The model entities can be further distinguished on the micro level as well as macro level.

(4.1) Micro Level: On the local level of model entities, an explicit overview of the agents' behavior should be provided, e.g. in terms of agents' learning capabilities and adaptivity, different classes of agents, and so forth. This explicit micro level foundation of the model allows drawing the connection to already existing findings that are strongly related to the research question (e.g., findings in behavioral science when dealing with agents as individuals, findings from market structure analysis when dealing with markets, findings from organizational theory when dealing with groups or departments, etc.).

(4.2) Macro Level: In addition, accurate information on the general environment and topology should be provided, such as information of how agents are connected to each other (in terms of network structure, spatial distribution, subgroups, etc.), and also basic information such as the size of the agent population. In many cases, macro level parameters are varied explicitly within simulations (density of networks, group size, spatial distribution, etc.). Thus, providing information on how the system entities on the macro level are developed allows to draw the connection, and to assess the appropriateness according to previous findings such as research in network science.

(5) Model Input: As noted in the previous section, two important criteria are relevant to assess and replicate published models: a list of all model input parameters with their respective range of parameter values and statistical distribution (normal distribution, uniform distribution, skewed distribution, etc.). However, while a full list of parameters are regularly presented in published manuscripts, the precise range of possible values as well as their distribution is systematically less often reported and independent of the journals' ranking. Presenting the full range of input values and modeled distributions allows to draw inferences on the reasonableness of the formal model and the numeric inputs to the ABM. Thus, authors may provide a complete list of model parameters as well as their statistical distributions.

(6) Model Output: Complementing the presentation of input parameters of the model, a list of all output variables and their measurement should be reported. As noted previously, although the model output is stated verbally in almost all analyzed articles, the mathematical algorithm to compute the output was systematically less often reported, and impedes the understanding of all following analyses. For example, when measuring the speed of diffusion, authors could report a variety of different measures which could be based on averaged values of all simulation runs regarding market penetration, the time until diffusion take off in the first quartile, or maybe the diffusion rate among different quantiles (Delre et al. 2006; Goldenberg et al. 2001). All of these measures are suitable, but a concise mathematical notation is crucial for evaluating models and their specific implication. Thus, presentation of the formal algorithm to compute all output variables is essential to thoroughly understand and / or replicate ABMs.

(7) Procedural Overview of the Model: Finally, a flowchart or any graphical representation of the model has been proven useful in understanding the general procedure of the model, and how the system as a whole is updated across simulation runs (Grimm et al. 2010). This graphical step-by-step presentation is particularly helpful for complex models with a large number of parameters or complex updating procedures (e.g., changing updating rules dependent on the state of the system, etc.). Thus, authors may provide a graphical overview of the model on how the simulation steps are conducted and how algorithms relate to each other on a process perspective.

At the end of this second subsection regarding the computational implementation of the conceptual model, a mutual understanding of the theoretical background (subsection one) and its computational implementation (subsection two) is assured.

4.3 Model Execution and Analysis

(8) Model Initialization: The initial step in the model execution and analysis subsection is the initialization of the ABM. The process of initialization consists of assigning starting values to all model entities (i.e., micro and macro level). This initial step is crucial for replicating simulation results, and the result itself usually depends on the starting values of the model, such as the number of initial adopters within a network when modeling diffusion dynamics. Thus, authors should clearly define how the model was initialized, and if model initializations are varied during computational experiments (Lorscheid et al. 2011). Providing information on the initialization of the model allows other researchers to conduct replication studies, and to encourage follow up studies.

(9) Model Verification: Furthermore, the computational model has to be verified in terms of its representation of the underlying conceptual model. Herein, the ultimate goal of model verification is to ensure that the computational model and implemented algorithms work appropriately, and are accurate and error-free. Lending from software engineering, the process of model verification can be conducted similarly by structured code walkthroughs, debugging procedures, and unit case analyses, among others (see North and Macal (2007) in detail). However, although the process of model verification is an important step to falsify a model, this not necessarily means that a model which passed all conducted verification tests addresses (1) a relevant problem, neither theoretically nor practically, or (2) captures the real-world phenomenon appropriately (see guideline 11 on model validation in further detail).

Unfortunately, only a small fraction of publications provides information on how model verification was assured and which tests were conducted. Since all analyzed submissions in the previous section have been published in top tier journals, this is not surprising—however, providing complementary information on verification procedures is ceteris paribus rather beneficial than unbeneficial for manuscripts, and strengthen rather than impede the signaling effect regarding authors' cautiousness during the process of model building and testing.

(10) Computational Experiments: The final step in the execution and analysis subsection is related to computational experiments with the model. Only a systematic analysis of the model, and appropriate standards in presenting the simulation setup and results, will allow inter-subjective verifiability among researchers in the scientific

community. Computational experiments can be conducted by applying the principles of classical experimental designs, as initially developed by Fisher (1971). Principles for experimental and fractional factorial designs allow an in-depth analysis of how parameters interact with each other, which are the most important ones among all other parameters, in which area of parameter values model results are robust, and for which range of parameter values the model tends to degenerate, etc. (Lorscheid et al. 2011). Only systematically conducted experimental designs allow for testing of such effects and the analyses of particular parameters while holding others constant, and how interactions between parameters influence the measured model outcomes. However, such experimental designs are “not used as widely or effectively in the practice of simulation as it should be”, and “seem to ignore the basics of experimental design” (Richiardi et al. (2006), section 1.5). Thus, using concise experimental designs to conduct computational simulations enhances the overall quality, credibility, and assessment of the models’ behavior (see Lorscheid et al. (2011) forfurther details).

Overall, this final step in model execution and analysis adds up to a sound theoretical foundation of the model (first subsection), its conversion from theoretical constructs and concepts into mathematical language and algorithms (second subsection), and the rigorous testing of how the computational model and its parameters interact with each other (third subsection). How well the final model then fits with respect to the real-world phenomenon is part of the final subsection.

4.4 Model Assessment and Documentation

(11) Model Validation: The validation of the ABM assesses how well the model captures the real-world characteristics of a particular phenomenon. Thus, to validate an ABM, the model results are ultimately compared to the empirical real world. Herein, several types of validity can be assessed:

(1) First, the models’ face validity can be assessed, which means that the model is compared on a more general level as to what extent the model results “seem plausible […] and look right” (North and Macal 2007, p. 227). This could be evaluated by comparing the model results to what would be expected from a theoretical stand point (Epstein 1999).

(2) Secondly, in contrast to this more qualitative assessment, the model can also be directly compared to existing empirical results in terms of its external empirical and predictive validity. Similar to procedures in the area of machine learning algorithms, models can be calibrated on part of the empirical data, and then tested against a hold out sample (Kleijnen 2008). This evaluation can also be made in more strict statistical terms by conducting tests between both sample distributions, and to test if the models' outcome distribution is sufficiently close to the empirical distribution (Kleijnen 1995).

(3) In addition, besides assessing models in terms of their face or empirical and predictive validity, a model can also be compared to previous models in the same domain, in terms of convergent validity of the model. This is important as it allows researchers to build on previous models and to apply Occam's Razor: when comparing models against each other, less complex models with lower number of parameters may generally be preferred as long as both models are equally strong in their theoretical foundation and describe the real-world phenomenon equally well (e.g., in terms of their empirical and predictive validity).

Thus, providing information on how the ABM is compared to relevant real-world properties, and how the model deviates from (or is in line with) previous research is of fundamental interest in the validation process.

(12) Model Documentation and Archiving: The last point of our guidelines is related to the dissemination of new knowledge through new ABMs within the scientific community. In particular, we suggest that authors make their models publicly available—e.g., through new platforms such as openabm.com, journal repositories, or hosted on the authors' own servers. A more explicit documentation and publicly available archives for ABMs would be beneficial for at least three reasons: (1) replication studies of other researchers to build on the published model, (2) allowing the scientific community to fully understand the models' procedure, and to encourage discussion on improvements if necessary, and (3) using published models in graduate classes to encourage students in transferring theoretical concepts and natural language into mathematical language and algorithms (these points are discussed in greater detail in the discussion section at the end of our article). Thus, although authors would considerably increase their own vulnerability when fully documenting and publicly archiving their ABM, it nevertheless would strengthen the published models' credibility, and the credibility of ABM as a new research method (see also Nan 2011).

5. Example — Viral Marketing Dynamics in Social Networks

To illustrate our proposed set of guidelines, we will now present a brief application of an ABM to model viral marketing campaigns in social networks. Our ABM examines how the dynamics of social networks and heterogeneous preferences among individuals affect the performance of viral marketing campaigns. Our results support and replicate previous findings regarding optimal seeding strategies in social networks, but also provide additional evidence under which conditions particular seeding strategies may backfire.

5.1 Theoretical Background and Related Work

Consumers are increasingly interconnected online and past research provided solid evidence that consumers rely heavily on advice and recommendations from such networks when making purchase decisions, and companies use viral marketing strategies among consumers to encourage new product adoption (Hill et al. 2006; Iyengar et al. 2010). Furthermore, past research also provided evidence on how to manage such campaigns effectively: while a stream of behavioral consumer research advanced our understanding on how motivational drivers, reward types, or feedback characteristics influence the performance of such campaigns (e.g., Chevalier and Mayzlin 2006), a second modeling and management science oriented stream emerged, developing new statistical models for predicting choice behavior and word-of-mouth in such dynamic environments (e.g., Dellarocas and Narayan 2006). At the same time, companies are shifting their budgets from traditional media channels toward social media and viral marketing campaigns, thus, reflecting the strong need to derive effective viral marketing strategies (Bampo et al. 2008). However, companies launching such viral marketing campaigns face the challenge of selecting the right individuals to maximize particular business objectives such as fast awareness of a new product in the market and decreasing adoption time of new services and products (Iyengar et al. 2010).

To manage such campaigns effectively, Bampo et al. (2008) proposed a decompositional approach of viral marketing activities consisting of three main aspects: (1) the particular structure of the social network, (2) the behavioral characteristics of its constituting members, and (3) the seeding strategy to initiate the viral process.

We will build on Bampo et al.'s (2008) decompositional approach to study the dynamics of these components in viral marketing campaigns and model such interactions based on an ABM. We make use of the ABM methodology due to the special nature of the empirical phenomenon of viral marketing campaigns since ABMs are well suited to study dynamic processes of a system as a whole (e.g., the speed of diffusion within a viral marketing campaign), based on the dynamics of social interactions and adaptive behavior of individuals.

5.2 Conceptual Model and Computational Implementation

5.2.1 Micro Level: Agent Behavior

To model the dynamics of viral marketing campaigns, we vary the individual behavior of agents, and how agents are interconnected.

Agents make a simple binary decision to adopt or not to adopt an advertised product—thus, an agent i makes a choice of the set $\Omega_i = \{0,1\}$. The derived utility of the product for agent i is due to a functional utility ($U(v_i)$), and a social utility ($U(s_i)$). Since individuals may differ in their degree of social susceptibility (e.g., Bearden and Etzel 1982), agents are heterogeneous regarding the weight of both utilities, captured by the individual weighting parameter w_i. Since adopting a new product is not without cost, individuals may also differ in their amount of perceived costs c_i (financially and socially—reflecting the different weights agents may assign to the functional and social utilities). Thus, agents finally adopt if, and only if, their weighted net utility is strictly positive:

$$\Omega_i = \begin{cases} 1, \text{ if } w_i \times U(v_i) + (1-w_i) \times U(s_i) - c_i > 0 \\ 0, \text{ if } w_i \times U(v_i) + (1-w_i) \times U(s_i) - c_i < 0 \end{cases}$$

Furthermore, agents may perceive individual levels of uncertainty regarding the "true" functional value of v_i. We account for such uncertainty by an agent specific parameter λ_i and scale agents total utility by applying a normalized von Neumann/Morgenstern utility function, known from standard choice modeling procedures (e.g., Hauser and Urban 1979). Over time, a focal agent i can learn from the behavior of an agent j in his personal network K_i who already adopted the product, $\{i|\Omega=0\} \leftarrow \{(j|\Omega=1) \in K_i\}$—as a result, the initial uncertainty λ_i is adjusted continuously (λ_i^{adj}) and decreases with increasing social interactions with other agents $j \in K_i$. To summarize, we model agents' functional utility according to:

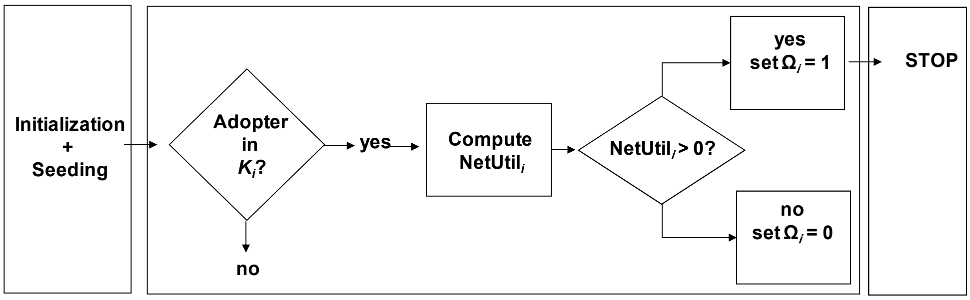
$$U(v_i) = \frac{1-\exp(\lambda_i^{adj} \times [(v_i^* - \underline{v})/(\overline{v} - \underline{v})])}{1-\exp(\lambda_i^{adj})} \quad \text{with} \quad \lambda_i^{adj} = \lambda_i - \lambda_i \times s_i$$

On a more precise level regarding agents' connections and social interactions, an individual agent i out of N agents has k_i connections to other agents j in his personal network $K_i \subset N$ and $j \in K_i$. Based on previous empirical work, we define connections among agents as symmetrical (Friedkin 1986), meaning that i may influence j and j may influence i equally such that $\nexists \{i,j\} \subset N := \{i \to j\} \vee \{i \leftarrow j\}$ holds. Such influence processes affect agents' social utility which is based on the influence of agents who already adopted the product relative to the influence of all agents in i's personal network. Specifically, the individual influence of j on i is based on his power π_j, approximated by j's popularity. In line with previous work (e.g., Barabasi and Albert 1999), we define popularity by the total number of friends (k_j) weighted to his relative distance to i (d_{ij}). We model distance based on Latané's (1981) social impact theory, meaning that the influence of j on i decreases with increasing distance. Furthermore, j's popularity may also depend on how many popular individuals j knows in his K_j. Thus, we model the social utility finally by

$$U(s_i) = \frac{\sum_{j \in K_i} \pi_j \,|\Omega = 1}{\sum_{j \in K_i} \pi_j} \quad \text{with} \quad \pi_j = \left(k_j \times \frac{d_{\max} - d_{ij}}{d_{\max}}\right) \times \left(1 + \frac{\sum_{\alpha \in K_j} a_{\alpha j} \,|\Omega = 1}{\sum_{\alpha \in K_j} a_{\alpha j}}\right)$$

A flowchart is provided in Figure 5 and summarizes our formal model development from a process based perspective.

Figure 5: Flowchart Regarding the Core of Agents' Behavior and Decisions



5.2.2 Macro Level: Social Structure

Building on Bampo et al.'s (2008) finding of a good fit of so-called small world and random network properties in a viral marketing campaign of a leading car manufacturer, we model the structural relationship among agents based on Watts and Strogatz's (1998) algorithm to interpolate between such regular, small world, and random networks. Herein, agents are connected on a two-dimensional lattice with k_i connections to other agents.

In a regular network, all agents only have a relationship to their nearest neighbor (see Figure 6 left). Watts and Strogatz's (1998) algorithm introduces a rewire probability r that allows cutting a tie with a close neighbor in such regular networks, and to create a new tie to an agent in a distant neighborhood. As a result, agents may have a considerable number of close, spatially proximate friends and some distant acquaintances living far away, reflecting the properties of real social networks (e.g., Granovetter 1973). Increasing the rewire probability r results in properties of random networks where agents have only sparse local networks. The interval of $(\underline{r},\overline{r}) = \{\underline{r} < r_{smallworld\_properties} \ll \overline{r}\}$ with $\underline{r} = 0$ and $\overline{r} = 1$, provides properties of small world networks where agents are highly locally clustered, and have a few connections to distant acquaintances. Thus, in this interval, we can develop small world networks with (1) high local clustering, and (2) some shortcuts into distant neighborhoods. Thus, we can interpolate between the extremes of regular networks with high clustering and no such shortcuts, and random networks with low clustering and many shortcuts across all neighborhoods (see Albert and Barabasi (2002) for details). Figure 6 provides three examples of these networks.

Figure 6: Modeling Regular, Small World, and Random Networks by Variation of Rewire Probability *r*

5.3 Experimental Design and Analyses

We conducted two computational experiments to assess the influence of agent heterogeneity and network structure on the performance of viral marketing campaigns. Experiments were conducted with a total of N = 412^2 = 1681 agents on a two-dimensional lattice. In the first experiment we manipulated the structural properties of the network (rewire probability *r*), different group sizes for company seeding strategies, and markets consisting of agents with higher weighting of either functional or social utilities. The second experiment takes a more detailed look at how large groups and differences in perceived costs influence campaign performance. Table 2 summarizes our model parameters and respective distributions. All simulations were initialized with a randomly chosen set of .005% agents that already adopted the product.

Table 2: List of Model Parameters and Statistical Distributions

Parameter	Distribution	Experimental Factor Levels
Manipulated Across Simulations		
w	Normal (μ;σ)	Experiment 1: {.15 (SD=.05); .85 (SD=.05)}
	Normal (μ;σ)	Experiment 2: {.15 (SD=.05)}
c	Uniform (25;50)	Experiment 1: {(25;50)}
	Triangular (μ; (Min;Max))	Experiment 2: {20 (Min=10; Max=60); 50 (Min=10; Max=60)}
rewire probability r	Constant	Experiment 1: {0; .05; .1; .15; .2; .4; .6; .8; 1}
	Constant	Experiment 2: {.15}
group size	Constant	Experiment 1: {4; 8; 12; 20}
	Constant	Experiment 2: {4; 8; 12; 20; 28; 36; 48; 68}
Constant Across Simulations		
v	Uniform (1;100)	
s	Uniform (1;100)	
lambda (λ)	Normal (1;.05)	

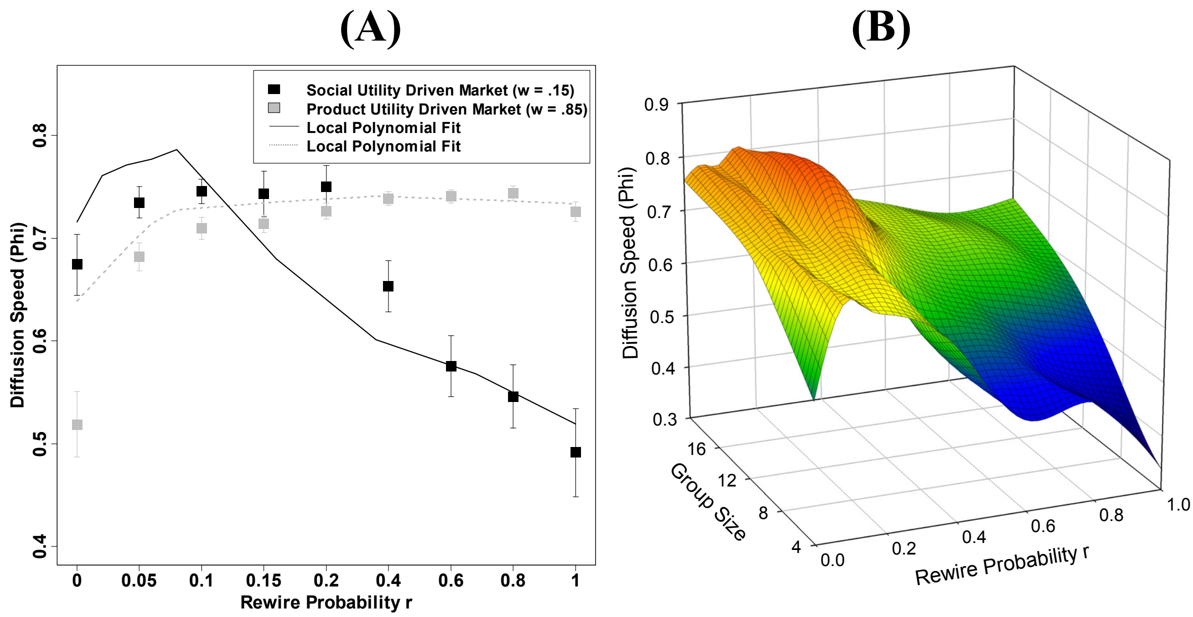
Our central dependent measure is campaign performance, approximated by measuring the speed ϕ of diffusion through averaging the cumulative distribution of adopters at time t ($D(t)$) over the total number of agents N (similarly, see Delre et al. 2006).

$$\phi = \frac{1}{t} \times \frac{\sum_{t=0}^{T} D(t)}{N}$$

Before we conducted all computational experiments, we applied model verification tests by tracing our model output and comparing the results to our manual calculations (see Wang et al. 2009). Our model results matched all manual calculations, supporting the accuracy of the ABM.

In the first experiment, we examined the influence of different network structures (rewire probability r), group size (8, 12, 20, 24), and type of markets (social utility driven vs. product utility driven) on the speed of diffusion. Figure 7A shows that the influence of network structure is dependent on the particular type of the market: we find that product utility driven markets replicate the results of Bampo et al. (2008) such that small world networks ($0 < r \leq .2$) and random networks ($r \gg .2$) do not differ strongly regarding their influence on the speed of diffusion. However, we find that social utility driven markets yield a systematically higher diffusion speed in the region of small world networks compared to all other network structures (see Figure 7A and 7B).

Figure 7: Effect of Rewire Probability and Market Type on Diffusion Speed (A), and Interaction Effect of Rewire Probability and Group Size on Diffusion Speed in Social Utility Driven Markets (B)



On a more detailed level, we tested these initial impressions statistically by applying linear regression models, and also used quantile regression models for the 10th, 50th, and 90th quantile to see if and how parameter values are changing for different quantiles of diffusion speed (Koenker and Hallock 2001). Table 3 shows a fundamental shift in model constants among different market types: a substantive interpretation of the model constants, while setting all other predictors equal to zero, reveals that social utility driven markets score larger compared to product utility driven markets in all regression models (e.g., in the linear model case: $\text{constant}_{social\_utility} = .601$ vs. $\text{constant}_{product\_utility} = .458$, $t(714) = 4.95$, $p < .001$). Furthermore, while the influence of rewire probability is positively associated with product utility driven markets ($\text{Beta}_{rewire;product\_utility} = .634$, $t(714) = 13.760$, $p < .001$), this effect is reversed for social utility driven markets ($\text{Beta}_{rewire;social\_utility} = -.35$, $t(714) = 5.998$, $p < .001$). Thus, while diffusion speed is increasing with higher rewire probability in product utility driven markets, we find that social utility driven markets are reduced in diffusion speed, indicating the lack of social pressure among agents to encourage product adoption. However, this effect is of quadratic nature with a global maximum for social utility driven markets and diminishing returns for product utility driven markets in both cases around $r \approx .2$ (as seen previously in Figure 7A and 7B). Finally, and enriching the previous visual inference for social utility driven markets, we find that social utility driven markets in contrast to product utility driven markets reveal strong effects on diffusion speed if both group size and rewire probability are increasing, particularly explaining larger quantiles of diffusion speed ($\geq 50\%$). Thus, this first experiment revealed that highly locally clustered networks in social utility driven markets may yield systematically higher diffusion speed rates compared to product utility driven markets.

Table 3: Effect of Group Size and Rewire Probability on Diffusion Speed for Social Utility and Product Utility Driven Markets

	Linear Model Estimates		Quantile Regression Estimates					
			10% Quantile		50% Quantile		90% Quantile	
Social Utility Driven Market (w = .15)	**Estimate *(SE)***	**t value**	**Estimate *(SE)***	**t value**	**Estimate *(SE)***	**t value**	**Estimate *(SE)***	**t value**
Constant	.601 *(.02)*	27.287***	.354 *(.06)*	5.940***	.670 *(.03)*	19.591***	.696 *(.02)*	29.121***
Groupsize (GS)	.060 *(.01)*	6.416***	.130 *(.02)*	6.041***	.037 *(.01)*	2.688***	.040 *(.01)*	4.929***
Rewireprobability (RP)	-.353 *(.06)*	-5.998***	-.264 *(.17)*	-1.595	-.462 *(.10)*	-4.743***	-.230 *(.08)*	-2.993***
RP x RP	-.144 *(.04)*	-3.480***	-.129 *(.08)*	-1.534	-.132 *(.07)*	-1.773	-.216 *(.05)*	-4.053***
GS x RP	.105 *(.02)*	5.626***	.063 *(.04)*	1.417	.137 *(.03)*	4.493***	.104 *(.02)*	6.387***
	R^2 = .71							
Product Utility Driven Market (w = .85)	**Estimate *(SE)***	**t value**	**Estimate *(SE)***	**t value**	**Estimate *(SE)***	**t value**	**Estimate *(SE)***	**t value**
Constant	.458 *(.02)*	26.545***	.272 *(.06)*	4.573***	.570 *(.01)*	47.860***	.611 *(.02)*	32.647***
Groupsize (GS)	.071 *(.01)*	9.692***	.105 *(.02)*	5.130***	.047 *(.004)*	10.810***	.041 *(.01)*	5.930***
Rewireprobability (RP)	.634 *(.05)*	13.76***	.967 *(.12)*	7.792***	.281 *(.02)*	10.141***	.242 *(.04)*	6.711***
RP x RP	-.426 *(.03)*	-13.144***	-.590 *(.07)*	-9.031***	-.181 *(.02)*	-10.304***	-.152 *(.02)*	-7.409***
GS x RP	-.053 *(.01)*	-3.618***	-.106 *(.04)*	-3.037***	-.023 *(.01)*	-3.137***	-.022 *(.01)*	-2.166*
	R^2 = .56							

*** $p < .001$, ** $p < .01$, * $p < .05$

To get a more nuanced picture regarding the role of group size and more or less high adoption costs (financially or socially), we conducted a second experiment in which we varied the number of agents per group and the perceived individual costs in social utility driven markets (see Table 2 above for an overview). In line with recent empirical research (see Huffaker et al. 2011), our results revealed that although the speed of diffusion is increasing with more agents per group, we found that if adoption costs are relatively high, larger groups may impede the speed of diffusion, indicating the lack of conformity among agents. Figure 8 already reveals the inverse u-shaped relationship of group size on diffusion speed for social utility driven markets with high adoption costs.

Figure 8: Effect of Group Size and Perceived Costs on Diffusion Speed

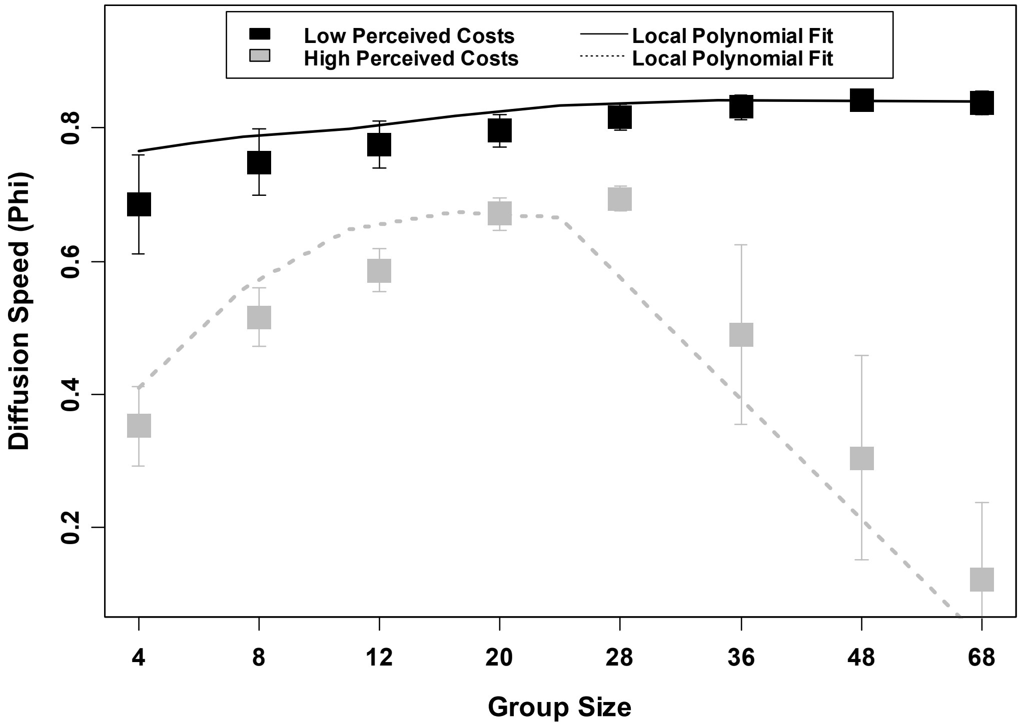


Table 4 summarizes our linear model results and shows the important influence of the quadratic group size parameter (see model 3), increasing the amount of explained variance from .48 to .60 ($F(1,315) = 97.194$, $p < .001$), as well as the significant negative interaction effect of perceived costs and group size ($Beta_{GroupSize \times PerceivedCosts} = -.11$, $t(314) = 6.991$, $p < .001$).

Table 4: Diffusion Speed Prediction by Group Size and Perceived Costs based on Linear Model Estimates

	Model 1 (Main Effects Only)		Model 2 (Interaction Effect)		Model 3 (Quadratic Effect)	
	Estimate *(SE)*	**t value**	**Estimate *(SE)***	**t value**	**Estimate *(SE)***	**t value**
Constant	.831 *(.03)*	27.349***	.679 *(.04)*	17.883***	.193 *(.06)*	3.242***
Groupsize (GS)	-.014 *(.01)*	-1.506	.041 *(.01)*	3.203***	.469 *(.04)*	10.459***
Perceived Costs (PC)	-.324 *(.02)*	-14.857***	-.021 *(.05)*	-0.383	-.021 *(.05)*	-0.438
GS x PC			-.110 *(.02)*	-6.121***	-.110 *(.02)*	-6.991***
GS x GS					-.078 *(.01)*	-9.859***
	R^2 = .41		**R^2 = .48**		**R^2 = .60**	

$F(1,316) = 36.463$*** (Model 1 vs. Model 2) $F(1,315) = 97.194$*** (Model 2 vs. Model 3)

*** $p < .001$, ** $p < .01$, * $p < .05$

Overall, our two computational experiments replicated previous studies on viral marketing campaign performance (e.g. Bampo et al. 2008), but also highlighted notable differences among different network structures and agents, the influence of varying group size, as well as perceived costs. Since the latter effects were found in some recent studies (see Narayan et al. 2011; Huffaker et al. 2011), we provided a simple model to study and predict diffusion patterns across different markets and heterogeneous agent populations.

5.4 Model Evaluation and Validation

We conducted comparisons of our simulation results to recent empirical research as well as similarities and differences to other simulation studies. In essence, our results and the pattern of relationships regarding the influence of different network structures is in line with recent research on increased diffusion speed in small world networks (e.g., Delre et al. 2006). However, we provide evidence that these results may differ across different types of markets such as more social utility driven markets, in contrast to more product utility driven markets (e.g., see also Bampo et al. 2008). Furthermore, we also found the same diminishing returns effect regarding the influence of large groups on consumers' probability to adopt the respective product as in recent work (Huffaker et al. 2011). Even more importantly, our result is not only in line with current viral marketing research but also on a more fundamental level regarding the decreasing influence of additional members on consumers' preference revision rules found in recent research (see Narayan et al. 2011). As a result, our model specifications and agents' sensitivity to social influence (weighting parameter *w*) can be adjusted to a large variety of situations, controlling for individual differences across agents. Thus, our model replicates a variety of patterns compared to previous studies but also provides additional evidence for possible boundary conditions and moderating effects.

5.5 Discussion

The contribution of our model is three-fold: (1) Our model provides an alternative explanation to aggregate diffusion models—thus, instead of assuming equal susceptibility to peer influence among all individuals of the population as in standard diffusion models (see Peres et al. 2010 for a detailed and recent discussion), diffusion processes can be explained and modeled based on individual level information such as preferences, attitudes, and network data, which is increasingly available. (2) We developed an ABM which is also explicitly linked to fundamental concepts and theories in behavioral and social science research (social impact theory, risk-adjusted utility functions, different network structures, and so forth)—as a result, our model can be directly linked to experimental and survey based research to empirically calibrate model parameters. (3) Finally, our model is scalable to a number of problems, and is able to replicate previous empirical findings regarding differences in diffusion rates among market types as well as offering interesting avenues for future research such as testing the interactive role of susceptibility to peer influence, and adoption of different technological generations to explain leapfrogging behavior among consumers.

6. General Discussion

We will now discuss more generally the implications of our proposed guidelines for ABM based research, the methodological implications for a triangulation with different research methods, implications for graduate education, and for assuring publication quality in IS research.

6.1 Implications for ABM Based Research

Our proposed guidelines are intended to influence future ABM applications in two ways: first, future models that consider the use of our guidelines may benefit from a more theoretically driven model building and as a result, increase the credibility in the ABM methodology due to a strong underlying theoretical framework, and further, may profit from the rigorous use of the methodology. As a result, authors can more precisely stress their contribution to the current stream of theoretical, empirical, or previous computational work. Thus, authors may explicitly build on a well known theoretical or computational model but extend it, for example, with a missing theoretical concept.

Secondly, our notion to more explicitly report the conceptual model in a strict mathematical way as well as to report the way how computational experiments were conducted (e.g., parameter values, parameter distributions, seeding strategies, etc.), will not only be beneficial for a precise evaluation for reviewers since vague natural language can be clarified. This explicitness in model building will also be beneficial for future work to build on already existent models which can be extended to new phenomena, or to include a missing theoretical concept as noted earlier.

Thus, our proposed guidelines are intended to facilitate a more rigorous way of how to build such ABMs, and to communicate them effectively.

6.2 Methodological Implications

As it has been stated that IS research is in need for a more pluralistic research methodology (Mingers 2001), ABMs can complement both positivist quantitative and interpretative qualitative research methods. As the cited research in the previous sections have shown, these computational models can be utilized to enable the link between more traditional research methods. In particular, qualitative research methods may initially help to understand the general context of the empirical phenomenon at a holistic and constructivist level. Researchers could make use of the ABM methodology to include a more dynamic perspective to the current phenomenon and simulate potential developments based on the findings of previous research such as case studies. As the particular field evolves over time, econometric methods can be used for empirical parameterization and calibration of the ABM. Thus, input parameters can be based explicitly on the results of previous statistical methods, and used to simulate possible developments over time or study interactions among the unit of analysis, which is usually not possible in a real setting.

Thus, ABMs have the potential to contribute to more traditional research methods, and to uncover interesting patterns of influence due to their inherent dynamic nature (i.e., interactions among agents, learning capabilities, etc.), as well as to generalize their findings on a broader level and for a wider range of possible cases which have not or actually cannot be studied in an empirical setting. Our proposed guidelines are developed to account for such a more pluralistic perspective along the process of building and testing ABMs.

6.3 Implications for Graduate Education and Curricula

Our framework of guidelines is also of importance for graduate education and university curricula. In essence, our proposed guidelines will allow students to develop, test, and communicate own ABM applications in an effective and rigorous way, as well as to allow supervisors to judge their work based on these guidelines. Furthermore, in the case that future work finds our proposed guidelines helpful, well-documented and rigorously developed ABMs can be used as a starting point for students' own model developments. In addition and at a more general level, this will also help to train students in applying theoretical concepts to the level of computational programming languages, and the way natural language and abstract concepts can be computationally implemented. As a result, we expect that ABMs may also help to facilitate a precise understanding of given theories since such computational implementations will hardly be possible without a precise understanding of its underlying concepts (for a broader discussion on the potential transfer of programming skills on other domains see Salomon and Perkins 1987).

6.4 Implications for Quality Control in IS Research

Finally, we also see notable implications of our proposed guidelines for quality control in IS publications. In particular, our guidelines may facilitate and assure the quality of presenting ABM based research along the publication process. Since we have shown the large heterogeneity in reporting of simulations results, and how computational experiments were conducted, these guidelines provide a list of general requirements for rigorous ABM research that ensures the quality in top tier IS publications. Thus, these guidelines may reduce redundancy among publications due to theory driven model building, and comparisons to previously published model results. As a result, such rigorously developed ABMs will not only increase the reliability and validity of findings but also ensure the necessary inter-subjective verifiability and high quality in IS publications.

Evidence from other disciplines provide considerable evidence that such guidelines strongly improve the quality of publications: for instance, medical research publications were lacking precise information regarding randomized controlled clinical studies a decade ago—as a result, the reliability and validity of such studies were questionable (Moher et al. 2008). Today, leading medical science and health research journals agreed upon strict guidelines on how to conduct and report clinical trials, which in turn positively affected the journals' quality in terms of a reduction of ambiguous language and validity of statistical results (Kane et al. 2007). We find similar developments in other fields such as statistical reporting guidelines in psychology (Wilkinson 1999; Cumming et al. 2007), or converging agreement on how to conduct accurate willingness-to-pay studies in the area of marketing research (Miller et al. 2011).

7. Conclusion

ABMs offer an important potential for a rapprochement of the current methodological poles of traditionally either qualitative interpretative-based or quantitative variance-based research methods. However, the way of building, analyzing, and validating ABMs is largely heterogeneous, and our analyses of recent ABM applications have shown that this heterogeneity is not exclusively attributable toward a journal's quality. Our proposed guidelines are intended to facilitate the development of broadly accepted modeling standards, and the way such models are built, analyzed, and validated. Thus, relying on clear standards for such a new methodology will help to unfold its full potential for a rigorous IS research, and finally increase the credibility in this new stream of computational research methods.

Appendix – List of Analyzed Articles

Author(s)	Year	Title	Journal
Adomavicius et al.	2008	Designing Intelligent Software Agents for Auctions with Limited Information Feedback	Information Systems Research
Bampo et al.	2008	The Effects of the Social Structure of Digital Networks on Viral Marketing Performance	Information Systems Research
Bichler et al.	2008	A Computational Analysis of Linear Price Iterative Combinatorial Auction Formats	Information Systems Research
Chang et al.	2010	A Network Perspective of Digital Competition in Online Advertising Industries: A Simulation-Based Approach	Information Systems Research
Nan	2011	Capturing Bottom-Up Information Technology Use Processes: A Complex Adaptive Systems Model	MIS Quarterly
Weitzel et al.	2006	A Unified Economic Model of Standard Diffusion: The Impact of Standardization Cost, Network Effects, and Network Topology	MIS Quarterly
Cowan et al.	2007	Bilateral Collaboration and the Emergence of Innovation Networks	Management Science
Hanaki et al.	2007	Cooperation in Evolving Social Networks	Management Science
Lin and Demirkan	2007	The Performance Consequences of Ambidexterity in Strategic Alliance Formations: Empirical Investigation and Computational Theorizing	Management Science
Linn and Tay	2007	Complexity and the Character of Stock Returns: Empirical Evidence and a Model of Asset Prices Based on Complex Investor Learning	Management Science
Rahmandad and Sterman	2008	Heterogeneity and Network Structure in the Dynamics of Diffusion: Comparing Agent-Based and Differential Equation Models	Management Science
Adler et al.	2011	A complexity perspective on collaborative decision making in organizations: The ecology of group-performance	Information & Management
Vahidov and Fazlollahi	2004	Pluralistic multi-agent decision support system: a framework and an empirical test	Information & Management
Canessa and Riolo	2006	An agent-based model of the impact of computer-mediated communication on organizational culture and performance: an example of the application of complex systems analysis tools to the study of CIS	Journal of Information Technology
Schramm et al.	2010	An agent-based diffusion model with consumer and brand agents	Decision Support Systems
Wang and Tadisina	2007	Simulating Internet-based collaboration: A cost-benefit case study using a multi-agent model	Decision Support Systems
Wang et al.	2009	An application of agent-based simulation to knowledge sharing	Decision Support Systems
Zaffar et al.	2010	Diffusion dynamics of open source software: An agent-based computational economics (ACE) approach	Decision Support Systems
Habib	2008	The Dynamics of Knowledge Creation Within Innovation Process From Case Studies to Agent Based Modelling	ICIS
Johnson and Faraj	2005	Preferential Attachment and Mutuality in Electronic Knowledge Networks	ICIS

Kathuria et al.	2011	Acquiring IT Competencies through Focused Technology Acquisitions	ICIS
Kraut and Ren	2007	An Agent-Based Model To Understand Tradeoffs In Online Community Design	ICIS
Lin and Desouza	2010	Co-Evolution of Organization Network and Individual Behavior: An Agent-Based Model of Interpersonal Knowledge Transfer	ICIS

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09/2009	**Northwestern University – Kellogg School of Management** Visiting Student
10/2004 – 10/2009	**University of Trier** Study of Business Administration (with Distinction) Quantitative Market Research; Innovation Mgmt.; Social Psychology
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Work Experience

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