

# **Three Essays on the Marketing of Innovations:**

## ***Community Collaboration, Strategy at Product Launch, and Customers' Post-Adoption Experience of Really New Products***

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vorgelegt von  
Christian Siegfried Anton Nagel, M.Sc.  
geboren am 18.09.1988 in Erding

Karwendelstraße 15  
81369, München



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Wirtschaftswissenschaftlichen Fakultät  
der Universität Passau

Erstgutachter: Prof. Dr. Jan H. Schumann  
Lehrstuhl für Betriebswirtschaftslehre  
mit Schwerpunkt Marketing und Innovation  
Universität Passau

Zweitgutachter: Prof. Dr. Dirk Totzek  
Lehrstuhl für Betriebswirtschaftslehre  
mit Schwerpunkt Marketing und Services  
Universität Passau

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# Summary

Really new products frequently receive great academic, managerial and public attention, because they have the potential to change everybody's lives. Our economic system fundamentally relies on creative destruction, i.e. the constant process by which innovations challenge established products. This tension between the new and the already existing in the end promises competitive advantage, but makes it difficult to successfully introduce product innovations to the market. Hence, companies strive to become better all along the innovation process, ranging from idea generation, to product launch, and customers' post adoption product experience. This dissertation addresses challenges along the product innovation process in three independent essays.

Essay 1 focuses on members' collaboration behavior in innovation forums. Many innovations at first are invented by users and later on get developed into products ready for the consumer market within firms' R&D departments. Users are often the first to encounter novel needs and come up with ideas, concepts and even prototypes to satisfy them. Online forums are social spheres where hobbyists and professionals from all over the world meet to exchange their ideas about products and share their latest experiences. Hence, online forums represent incredibly rich resources to inspire companies' ideation processes. Essay 1 investigates the social mechanism of member collaboration in innovation communities. Theory on creativity postulates that the interaction between the core and the periphery of social networks enables the communities' innovative performance. Recent research showed that members from the periphery can boost their individual innovative performance via exchanging with the community core. However, we still do not know why core members assist peripherals. Essay 1 reveals that core members benefit from exchanging with members from the periphery throughout increasing their own influence as experts among peers in the core. The identified mechanism can be used to select the right candidates for co-creation workshops.

Essay 2 identifies a product launch strategy for innovations which are both, radical and disruptive. The successful launch of radical and disruptive innovations is a difficult challenge, because their radical newness provokes consumers' uncertainties. Furthermore, because of their disruptiveness, at the time of product launch those innovations are perceived to be inferior regarding their primary functionality compared to established products, although their performance in general is fully sufficient to satisfy

consumers' actual needs. A means to address the perceived inferiority is to add a feature to the innovation which offers a functional surplus by means of existing technology. Essay 2 shows that simultaneously introducing the innovation and a functionally modified version thereof increases consumers' adoption intentions. Furthermore, consumers who opted for the modified, but more expensive version are not dissatisfied with their choice in the long run, although they do not need the additional performance from an objective point of view. Essay 2 contributes insights regarding the causes and consequences of this new product launch strategy to the theory of radical and disruptive innovations. The findings of this essay are highly relevant to managers, because they show how this strategy can be implemented in practice to lower the failure rate of really new products at product launch.

Innovation research to date is rich on evidence regarding the determinants of consumers' adoption decisions. However, perhaps due to questions of data accessibility, insights of consumers' post-adoption product evaluation are still scarce. Hence, essay 3 shifts the focus beyond product adoption to investigate the interplay of early adopters' experienced utility, perceived aesthetic value and attitude toward the product in the long-run. Findings show that the perceived aesthetic value creates a halo effect in the post-adoption phase, such that the influence of early adopters' experienced utility on attitude gets weaker, the more positively they evaluate the innovations' aesthetics over time. Furthermore, the halo effect only tempers the relationship between experienced hedonic utility and attitude when consumers are characterized by innate consumer innovativeness. Managers should see the products' form not only as a means to increase purchase intentions, but understand that aesthetic value offers the potential to shape consumers' long term attitude toward the product, which in turn is an important driver for word of mouth behavior. A high score on the trait innate consumer innovativeness is an appropriate criterion for the selection of users for design co-creation.



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## List of Abbreviations

EIPET	Evening Out Inferior Performance using Existing Technology
ICI	Innate Consumer Innovativeness
R&D	Research and Development
RDI	Radical-Disruptive Innovation
RDIMB	Radical-Disruptive Innovation Modification Bias



# 1. Introduction

## 1.1. Developments in Innovation Marketing

The successful introduction of product innovations to consumer markets is at the heart of innovation research. However, especially when introducing technological innovations, there is still a failure rate of 42 percent at product launch (Castellion & Markham, 2013). A large number of product innovations fail right after their introduction, either because they do not meet consumers' actual needs, or because they evoke uncertainties (Ram & Sheth, 1989). Given that innovation is vital in today's fast changing and highly competitive business environments, and given that companies make big investments in R&D in order to keep up with the pace of their competitors, the high failure rate at product launch remains a serious challenge for innovation practitioners and researchers alike. In order to help managers to reduce the risk of new product failure, innovation research has produced valuable insights in the last decades which lead to important developments in the field.

First, a remarkable development in the field of innovation research is the shift from innovation inside the firm to open innovation (Chesbrough, 2006), user- and open collaboration innovation (Baldwin & Hippel, 2011). Open innovation means the organizational permeability during the entire innovation process. Whereas the traditional approach to innovation was focused on keeping insights secret and protecting them by means of intellectual property rights, research acknowledged that firms can increase their innovative performance throughout licensing intellectual property and becoming open to suggestions during the research and development process (Chesbrough, 2006). The concept of user innovation acknowledged, that radical breakthroughs by far are much more likely to be discovered outside of the firms' organizational boundaries than within the R&D department (Hippel, 1986; Lüthje & Herstatt, 2004). Users are the first to face a particular need. Because of their usage experience, they often have valuable ideas how to satisfy their novel needs. In lack of solutions at the market, they become inventive themselves. The needs of these Lead Users foreshadow future market demand, because they become relevant to the majority of consumers in a particular market over time (Hippel, 1986). Hence, companies strive to identify those consumers and invite them to co-creation workshops (Enkel, Gassmann, & Chesbrough, 2009). Users exchange in online communities to share their latest product usage experiences, but also

to articulate their needs and exchange about potential product improvements (Franke & Shah, 2003). Online forums are a rich resource for ideation and several methods have been developed to identify users with creative capabilities. These methods, applied in research as well as innovation practice, comprise qualitative approaches like netnography as well as quantitative methods like pyramiding and social network analysis (Belz & Baumbach, 2010; Hippel, Franke, & Prügl, 2009; Kratzer, Lettl, Franke, & Gloor, 2016).

Second, we now witness a renaissance of academic interest in understanding consumers' barriers in new product adoption. Talke and Heidenreich (2014) note that innovation research has been affected by a pro-change bias, i.e. the idea that consumers embrace novelty. Innovation research in the tradition of the diffusion of innovations theory is deeply rooted in communication science (Rogers, 1995). Its view on innovation adoption hence has been biased toward the effectiveness of persuasion. In simple words, as long as products offer a significant relative advantage, attempts to educate consumers regarding the products' ease of use will eventually result in adoption intentions, because consumers love the new. However, recent research recently re-discovered that many consumers will never consider purchasing a particular product innovation, although companies keep spending on advertisements and public relations to provide education about the benefits and usefulness of their products. The new always comes at the price of the uncertain and consumers implicitly seek to avoid change (Talke & Heidenreich, 2014). In order to effectively reduce the high failure rate at product introduction, research needs to find ways to overcome consumers' hurdles in the innovation adoption context.

Third, the role of consumers' subjective evaluations during new product adoption became increasingly relevant. Traditional innovation research approached innovation adoption using the concept of consumers as rational decisions makers. This concept produced important insights regarding the determinants of new product adoption. However, by focusing on rational aspects like the innovations' relative advantage, perceived usefulness, usability, innovation research missed out to account for consumers' subjective, sensual experiences (Bagozzi, 1983). Especially innovations are products which provoke consumers' affects and lead to emotional reactions, like excitement or fear (Chaudhuri, Aboulnasr, & Ligas, 2010; Wood & Moreau, 2006). By underestimating the relevance of consumers' subjective impressions, innovation research also overlooked one of the most important drivers of purchase decisions in the modern consumer

culture: consumers' fun (Chaudhuri & Micu, 2014). Virtually all products, except for tools, offer functional as well as hedonic benefits. Hedonic utility means the consumers multisensory product appraisal, the fun during purchase as well as consumption (Voss, Spangenberg, & Grohmann, 2003). To increase sales and thus address the issue of the high failure rate at product launch, managers invest into product aesthetics. Aesthetic quality is a means to directly appeal to the consumers' senses before product adoption and even before product trial (Truong, Klink, Fort-Rioche, & Athaide, 2014). It communicates product functionality and fun to potential customers.

This dissertation addresses recent developments in the three delineated research avenues. It comprises three independent empirical essays which contribute insights along the innovation process ranging from product ideation to product launch and customers' post-adoption product experience. The first essay investigates why core members in innovation online forums exchange with members from the periphery of the implicit social network. The second essay identifies a product launch strategy for radical disruptive innovations and explores its underlying mechanism and consequences. The third essay focuses on the role of aesthetic value in the post-adoption phase.

## 1.2. Research Scope

### **Essay I: Is Talking to the Periphery a Waste of Time or the Road to Wisdom?**

The first study investigates the underlying mechanism of innovative performance in innovation forums. Innovation forums are social networks comprised of the exchange between its members (Kratzer et al., 2016). Hobbyists as well as professionals collaborate in online forums to make progress in their projects (Franke & Shah, 2003). Innovation research aims to identify what drives the innovative performance of these forums. Social networks can be structured into a community core and its periphery (Borgatti & Everett, 2000). Recent research argues that the innovative performance of the community is the consequence of the exchange between both structures the core and the periphery (Dahlander & Frederiksen, 2012; Rullani & Haeffliger, 2013). Although we have a lot of evidence that the creativity of the individual member is a function of its position in the network, to the best of my knowledge there is only one article so far systematically relating the individuals' network position to the vital macro core-periphery structure (Dahlander & Frederiksen, 2012). Dahlander and Frederiksen (2012) showed that members from the periphery have an incentive to collaborate with core members. The closer they get to the core, the greater their own innovative performance becomes. However, research so far offers no explanation regarding the counterpart of this potentially mutual relationship. Neither do we know why core members are willing to assist members from the periphery, nor do we know the process yielding this unknown benefit. The research questions addressed in the first essay are:

- (1) Do core members gain expert influence in the core by contributing to peripheral members?
- (2) What is the underlying process that improves core members' expert influence among their peers as the result of assisting peripheral members?

## **Essay II: Launching Radical Disruptive Innovations by Evening-Out Inferior Performance Using Established Technology**

The second essay identifies a product launch strategy and calls it Evening-Out Inferior Performance using Established Technology (EIPET). It is a strategy for introducing radical disruptive innovations to the market. Radical disruptive innovations (RDIs) are radical, because from the consumers' point of view they represent highly unfamiliar technologies. RDIs are disruptive because they are inferior regarding their primary performance compared to other products which are already established at the market (Christensen, 2016). In light of the finding that a majority of consumers is passively resistant toward novelty (Talke & Heidenreich, 2014), RDIs' radicalism as well as their inferiority compared to other products contemporarily fulfilling the same consumer needs create a difficult challenge for marketing managers when launching these kind of products. They hence sometimes simultaneously introduce a second version of the RDI, which offers an additional feature that evens out the RDIs inferiority by means of already well established technology. When BMW introduced the BMW i3 electric car at the end of 2013, they also offered a modified version with a small combustion engine to compensate inferiority regarding driving range that results when consumers draw comparisons between the new pure electric vehicle and traditional combustion engine cars. We do not know so far, if EIPET is an effective strategy to address consumers' passive innovation resistance.

- (1) Does EIPET weaken the influence of passive innovation resistance in consumers' decision processes?

Furthermore, RDIs are usually designed such that their performance is enough to fulfill consumers' actual needs. Hence, those consumers who pay extra to purchase the additional feature will not need the functional surplus most of the time. So far, we do not know if EIPET has long term negative effects on the consumers' attitude, product satisfaction or even word of mouth behavior.

- (2) How do consumers' ex-post insights into their true needs influence their post-adoption behavior?

### **Essay III: Post-Adoption Halo Effects of Aesthetic Product Evaluations and the Moderating Role of Innate Consumer Innovativeness**

The third essay investigates the interplay of perceived aesthetic value with experienced hedonic as well as functional utility in early adopters' post-adoption attitude formation processes. Innovation research pointed out that it is crucial to ensure that product innovations offer sufficient utility to consumers. However, recent research found that the products' aesthetic value can create a powerful halo effect in the adoption phase, reducing the relevance of product related information on the consumers' adoption intention (Hoegg & Alba, 2011). The aesthetic value is often even more relevant to convince consumers of the novel products' utility, than objective information. Consumers rely on visual cues, because they are a means to directly experience the product. Although managers apply the halo principle to increase adoption intentions, we do not know if they can count on a halo effect in the post-adoption phase as well. The first research question addressed is:

- (1) Is there a halo effect of perceived aesthetic value, buffering between product experience and attitude in the post-adoption phase?

Furthermore, Truong et al. (2014) showed that the influence of consumers' aesthetic product evaluation on adoption intentions systematically varies with innate consumer innovativeness. Because of this special relevance of aesthetics to innovative consumers, a potential halo effect in the post-adoption phase could also vary with consumer innovativeness. If the personality trait of consumer innovativeness would play a moderating role regarding the halo effect in early adopters' post-adoption attitude formation processes, managers could invite innovative consumers to co-creation workshops. The second research question is:

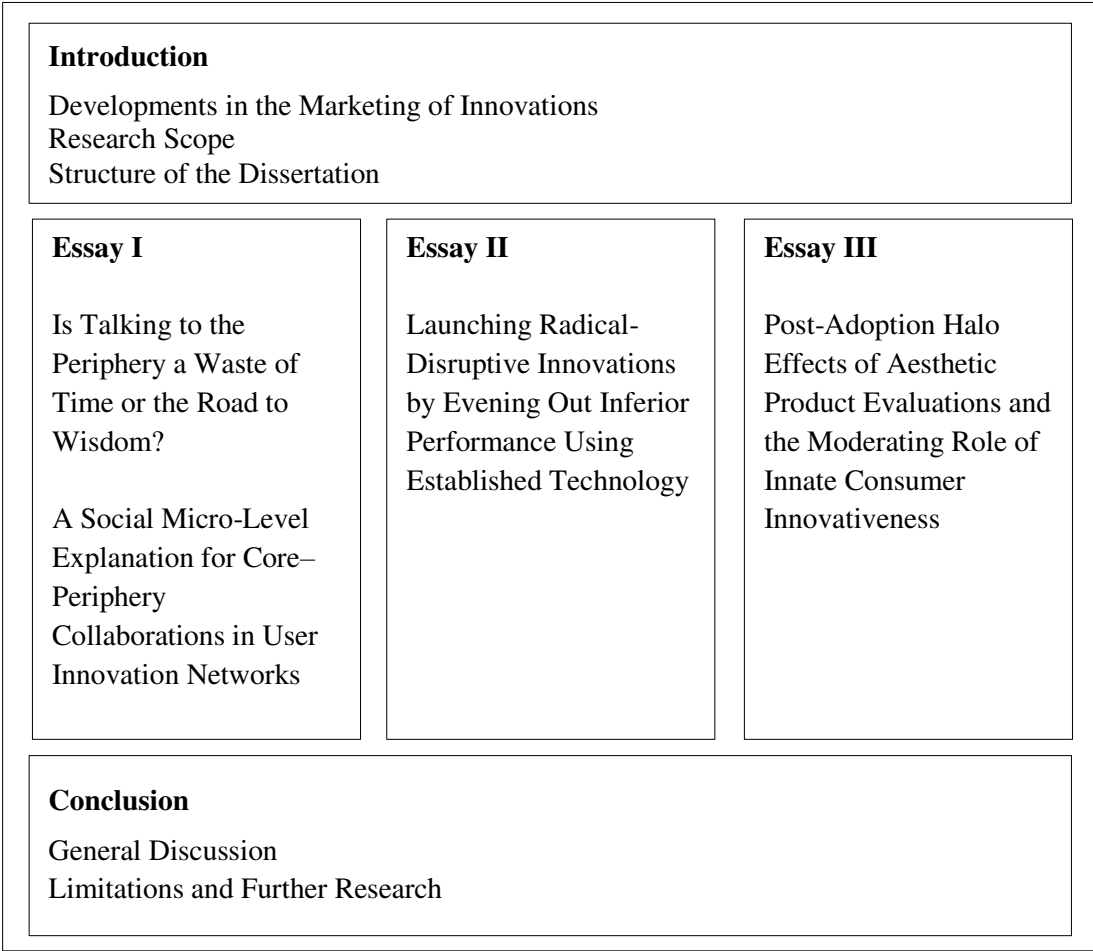
- (2) Does the potential halo effect vary in strength according to consumers' level of innate innovativeness?



1.3. Structure of the Dissertation

I illustrate the structure of this dissertation in Figure 1. In the next chapter, I present the essay on core-periphery exchange in innovation online forums and its effect on the core members’ expert influence. After that, I provide the essay on Evening-Out Inferior Performance using Established Technology (EIPET) in chapter 3. Furthermore, chapter 4 is the essay on consumers’ post-adoption halo effects of aesthetic product evaluations and the moderating role of innate consumer innovativeness. I finally discuss the limitations of this dissertation and suggest directions for further research in chapter 5.

Figure 1  
Structure of the Dissertation





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## **2. Essay I:**

### **Is Talking to the Periphery a Waste of Time or the Road to Wisdom?**

### **A Social Micro-Level Explanation for Core–Periphery Collaborations in User Innovation Networks**

Christian Nagel

*In both theory and practice, user-generated content in online forums is highly relevant to open innovation. This study therefore investigates how contact with peripheral members of a community influences core members' abilities to collaborate with other members in the core. Panel regressions and stochastic actor-oriented network models support analyses of longitudinal data pertaining to information exchanges in an innovative user forum. The findings indicate that core members who contribute to the periphery increase their abilities to cooperate with peers in the core; the more core members contribute to the periphery, the more contributions they make to peers in the core. The study also contributes to theory on innovative online communities by describing the process of causal periphery–core stimulation: As an outcome of the stimulation process, peripheral contacts increase core members' expert influence. Because people with high expert influence scores are valuable co-creation partners, open innovation managers are well advised to identify members who have the freshest ideas and invite them to co-creation workshops.*

## 2.1. Introduction

Hobbyists and enthusiasts from many backgrounds use online forums to share their experiences, exchange knowledge, and advance issues about which they are passionate. Open-innovation researchers have long recognized the relevance of user forums (Belz & Baumbach, 2010). Breakthrough ideas are far more likely to be discovered by users outside the organizational boundaries of firms than by engineers located within R&D departments (Chesbrough, 2006). The outcomes of user innovation activities range from new ideas to prototypes of new products ready to be produced for the mass market (Franke & Shah, 2003).

A community of creation consists of two parts: the core and the periphery. Exchanges between these parts are vital to the performance of innovative communities, but our knowledge about individual members' motivations to engage in such exchanges is scarce. Although research has shown that members of a periphery benefit from exchanges with core members, such that innovative performance is increased (Dahlander & Frederiksen, 2012), it has not explained how the decision process of this mutual relationship works at the individual level, that is, how core members might benefit from assisting peripheral members.

From a pessimistic view, it may seem to be a waste of time for individual core members to assist peripheral members. When they devote effort to answer peripherals' questions, the core members are distracted from contributing to the core, resulting in opportunity costs (Payne, Bettman, & Luce, 1996). From this perspective, such core-peripheral exchanges take place at the expense of core members. However, from a *rational choice* point of view (Braun & Gautschi, 2011), core members benefit from actively exchanging with peripherals. Because rational, utility-maximizing members balance the costs and benefits of their actions, core members exchange with the periphery because they profit from this type of behavior. Thus, if there are benefits to core members, the underlying process between core and periphery is symbiotic, and open innovation managers can intervene and reinforce the symbiosis to enhance community performance.

This research incorporates two previous findings. First, according to Franke and Shah (2003), social recognition is a key motivation for giving assistance. Members receive assistance from more knowledgeable peers and in turn use their own expertise to



contribute knowledge to others. Expert influence is a means of achieving social recognition; by assisting peripherals, core members strengthen their own influence. Second, the vast majority of peripheral members are passive recipients who simply follow core members' discussions (Rullani & Haeffliger, 2013). It is common for peripherals to enroll in forums only to solve single problems; when their problems are solved, they stop participating. The relevant peer group of core members resides in the core, not the periphery. Thus I argue, by helping peripherals, core members need to receive benefits that can be used to increase their social recognition in the core.

Using previous findings on members' motivations to collaborate in innovative online forums (Franke & Shah, 2003) and on the social determinants of creativity (Dahlander & Frederiksen, 2012; Perry-Smith & Shalley, 2003), I seek to answer two questions:

- (1) Do core members gain expert influence in the core by contributing to peripheral members?
- (2) What is the underlying process that improves core members' expert influence among their peers as the result of assisting peripheral members?

My theoretical contribution lies in clarifying the micro foundations of the macro process between core and periphery (Dahlander & Frederiksen, 2012, Rullani & Haeffliger, 2013). I propose that core members increase their expert influence among their peers by exchanging with peripheral members. I also identify the process that links contact with the periphery and expert influence in the core, by predicting that giving assistance to peripherals improves a core member's ability to contribute mindfully to other core members, which leads to greater expert influence.

The findings from a longitudinal study of member interactions in an innovative online community of hobbyist electric vehicle builders are generally in line with these predictions. Results of a fixed-effect panel regression reveal that core members' expert influence in the core increases when they increase their number of peripheral contacts. Furthermore, a mediation test indicates that the relationship between the number of contributions to the periphery and their expert influence in the core is fully mediated by members' reach in the core. Stochastic actor-oriented models establish the causality of this process and reveal that members' capacities to contribute to peers in the core change according to the numbers of their contributions to the periphery, but not vice versa.

In the next section, I provide the theoretical background of the study. Next, I derive hypotheses, describe the conceptual framework, and explain the sample and applied methods. I then detail how the study contributes to theory and offer implications for innovation practitioners. Finally, I discuss some limitations and directions for further research.

## 2.2. Theoretical Framework

### 2.2.1. The Social Side of Innovative Performance

*Innovation* is the outcome of a creative process that consists of reassembling existing knowledge from various sources in a new way to solve a problem (Perry-Smith & Shalley, 2003). The knowledge required to solve a particular problem can be acquired through social interactions and reception of cultural products. For example, a user in an electric car forum might confront the question of how much battery capacity is needed to build an electric vehicle that can cover a daily driven distance of 80 kilometers, given an electric engine with 60 A·h. The user may find the answer by asking peers and experts, reading articles or manuals, or watching tutorials. Creativity is a function of access to relevant knowledge; it is imminently social (Perry-Smith & Shalley, 2003). Social relationships can be expressed as networks (e.g., friends, advice-seekers, knowledge-exchangers). Research into the social side of creativity has shown that the degree of embeddedness of members in these networks greatly influences their individual creative achievements (Kratzer & Lettl, 2008, 2009) and the success of their innovations (Kratzer, Lettl, Franke, & Gloor, 2016). Members located in positions with high betweenness centrality tend to exhibit higher levels of creativity; they are brokers that connect parts of social networks that otherwise would not be in contact. Those located in such bridging social positions thus are exposed to greater amounts of non-redundant information. Kratzer and Lettl (2009) show that being a lead user relates positively to betweenness centrality in networks of school children. *Lead users* are consumers who experience needs long before the majority of the market (Herstatt & von Hippel, 1992; Urban & von Hippel, 1988). To satisfy these needs, they invent. Because lead users' needs and ideas foreshadow future market demand, firms search the Internet to identify them and integrate them into innovation projects (Hoyer, Chandy, Dorotic, Krafft, & Singh, 2010). Kratzer et al. (2016) show that in online communities, lead users have the greatest betweenness centrality.

Previous research also shows that individual innovative performance is socially co-determined; members of innovation forums collaborate to pursue their personal goals. My research differs from previous studies in that I account for members' embeddedness in the macro core–periphery context in which collaboration decisions are made at the micro level.

### 2.2.2. Methodological Individualism and the Core–Periphery Relationship

According to the logic of *methodological individualism* (Coleman, 1986), progress in social theories of action requires joint consideration of the macro and micro levels. Individual behavior at the micro level follows from macro phenomena that should be taken into account in efforts to explain the social behavior of individuals. Macro explanations follow from the aggregation of micro-level interactions among social actors. Therefore, understanding of micro-level interactions is a prerequisite for finding macro-level explanations. Despite the great number of findings that attribute innovative performance to the social embeddedness of members (Kratzer & Lettl, 2008, 2009; Kratzer et al., 2016), the question of individual innovative performance in online communities only recently has been approached with reference to the macro-level core–periphery distinction (Dahlander & Frederiksen, 2012; Rullani & Haefliger, 2013). According to the macro perspective, a social network can be partitioned into a core and a periphery (Borgatti & Everett, 2000). This core–periphery distinction is especially appropriate for analyzing innovation forums, because in online communities the vast majority of members are highly inactive; only a small core group truly exchanges on a frequent basis. In light of the core–periphery macro distinction, it is necessary to reconsider findings related to the relevance of the social embeddedness of actors. For example, searching for lead users by focusing on members with top betweenness centrality scores likely would lead to finding core members (Kratzer et al., 2016). As an illustration of this point, in the data used in this study, 72 percent of the core members belonged to the top 50 ranks in betweenness centrality. Furthermore, within the core, Spearman's rank correlation between the top 50 members according to coreness and the top 50 according to betweenness centrality was strong ( $r = 0.63$ ,  $p < 0.01$ ). Thus, individual innovative performance in small-world online networks is a consequence of coreness rather than individual centrality. I argue that though a shift of theory toward methodological individualism does not alter the correctness of existing implications (Coleman, 1986), theory development on innovative performance in online forums can make significant progress by taking the macro social context into account.

### **2.2.3. Motivation of Peripheral Members to Collaborate with Core Members**

The core is the place where the work is done. Highly active members exchange to make progress in their projects. The main benefit of close collaboration in the core is steady progress for everyone. However, close collaboration comes at the price of gradually converging ideas (Perry-Smith & Shalley, 2003); as collaboration becomes closer, ideas align, and the capacity for solving problems decreases, resulting in incremental innovation (Dahlander & Frederiksen, 2012). The periphery, in contrast, consists of mostly passive community members who have almost no relationship with one other and who seldom interact with core members. Therefore, it is the place where more radical ideas reside. Rullani and Haeffliger (2013) argue that both the core and the periphery are highly relevant in terms of innovation; at the macro level, the two parts mutually benefit. Core members set the social norms in online communities by means of their frequent and highly visible activities. Rullani and Haeffliger (2013) describe the core metaphorically as the stage in a theatrical play. Every now and then, peripheral members enter the stage to become involved in core member discussions and make valuable contributions. Peripheral members benefit from contributing to the core; the closer they get to the core, the stronger their innovative performance becomes (Cattani & Ferriani, 2008; Dahlander & Frederiksen, 2012). However, as in a theatrical play, it is the main actors on stage—the core members—who decide how to integrate peripheral contributors into the ongoing performance (Rullani & Haeffliger, 2013). Core members control their own activities; they actively decide when to create, maintain, or terminate a discussion with members from the periphery. I argue, therefore, that there is a process between core and periphery that motivates core members to help peripherals and grant benefits to both sides. Just as peripheral members profit from getting close to the core in terms of innovative performance, core members benefit from contributing to peripheral members in terms of expert influence in the core.

### 2.2.4. Motivation of Core Members to Exchange with Peripherals

A central motivation for assisting others in online communities and freely revealing knowledge is the *reciprocity norm* (Franke & Shah, 2003). Reciprocity is one of the shared values of members of innovative online communities. Members reveal their knowledge and assist others, because they expect their peers to return the favor when they find themselves in need of advice. Innovation forums are expert communities. Members who seek assistance frequently receive help from others who are more knowledgeable (Franke & Shah, 2003). Because of their high levels of capabilities, experts are the most sought-after contributors. Due to reciprocity, the *reputation* of being an expert is an intangible asset that increases the likelihood of receiving valuable information. A reputation is “a prevailing collective definition based on what the relevant public ‘knows’” (Lang & Lang, 1988, p. 84). Core members have a strong incentive for improving their reputations as experts. Reputation is so vital in innovation communities that its mechanism is frequently used by firms that search the Internet to identify lead users and integrate them into their innovation projects (Belz & Baumbach, 2010). Lead users have high levels of expert knowledge and are opinion leaders in their peer groups (Urban & von Hippel, 1988). *Pyramiding* relies on reputation, using ego network effects to identify lead users (von Hippel, Franke, & Prügl, 2009). It is a snowball-like process, in which members nominate others who are more knowledgeable such that members’ expert reputations lead from one member to another. Therefore, revealing knowledge to members of the periphery as an end in itself is unlikely to grant this kind of benefit. Peripheral members are mostly inactive, and many join only to ask one or two specific questions before leaving. I argue, therefore, that when members of online communities that are based on helping behavior build reputations over time, they build it among relevant peers from the core. With each contribution that core members make to the periphery, they increase their expert influence in the core (see Figure 2).

*H1: Core members’ contributions to the periphery increase their expert influence in the core.*

### 2.2.5. Novel Stimuli and Mindfulness

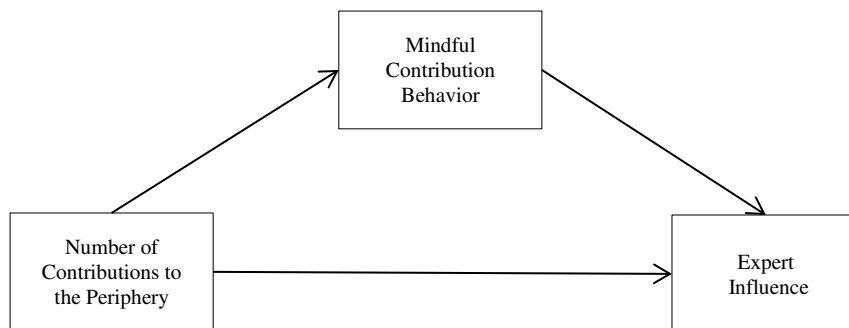
I expect this process, by which core members' contact with the periphery improves their expert influence in the core, to be a solution to a macro-level problem: Although the core is the social location in which the most experienced members meet, their problem-solving capacity decreases over time as their ideas become more similar (Dahlander & Frederiksen, 2012). As Perry-Smith and Shalley (2003) argue, contact with peripherals can foster creativity, because members of the periphery are socially less constrained in their thinking and therefore more likely to come up with radical ideas than core members. According to Weick and Roberts (1993), creativity is a collective achievement that originates from mindful interactions. When members of a social group heedfully interrelate, collective creativity emerges. Hagardon and Bechky (2006, p. 486) describe *mindfulness* as:

*“the amount of attention and effort that individuals allocate to a particular task or interaction. Participation in group interactions, as a result, becomes a product not of membership or presence within a group, but of the attention and energy that an individual commits to a particular interaction with others in the group.”*

Because I expect contact with the periphery to creatively inspire core members, I argue that having peripheral contacts increases core members' abilities to mindfully discuss issues in the core. Core members who maintain greater contact with peripheral members can put more attention and energy into their interactions with peers in the core. Reputation is earned by contributing something of significance to a great number of peers; it requires strong skills and original ideas. Franke and Shah (2003) note that reciprocity in online communities, unlike in other markets, is not simply quid pro quo. Rather, it is the outcome of a fairness game (Takahashi, 2000). Sharing knowledge with the community is perceived as fair; members who are perceived to be fair can expect to receive more assistance in the future. Maximizing the number of contributions to relevant peers is therefore an investment in reciprocity. I argue that the more contacts with the periphery a core member creates, the better the member's ability to contribute to the core. This relationship between inspiring conversation with the periphery and mindful contribution behavior in the core is likely to have a clear limit though. Beyond an optimal level, core members can assist peripherals with greater intensity only at the expense of a decrease in total reach.

*H2: (a) Mindfulness mediates core members' exposure to the periphery and their expert influence in the core, and (b) the relationship between members' amount of contacts to the periphery and the mindfulness of their contribution behavior in the core is inversely u-shaped.*

**Figure 2**  
Conceptual Framework (Essay I)



*Note:* Figure 2 illustrates that core members benefit from contributing to the periphery in terms of an increase in their expert influence among peers in the core. It further shows the underlying causal process between members' contact with the periphery and their influence in the core.



## 2.3. Methodology

### 2.3.1. Sample and Sampling

The data that I use in my study capture the social exchange pattern in an innovative online forum that focuses on converting combustion engine cars into electric vehicles. Despite the universally stated need for electric cars in modern consumer societies, product variety is still very limited, so consumers with engineering capabilities often construct their own electric vehicles to fulfill their needs. The online electric vehicle community has existed since 2007; it includes more than 40,000 members from all over the world. Its growth mirrors the increasing public interest in electric mobility.

I chose this particular forum because it does not have quality ratings or a defined core community. Some forums provide the possibility of directly rating the usefulness of a comment via a star rating. Such gamification features, however, come at the risk of shifting core members' motivations to assist others from personally profiting in terms of new ideas to solely maximizing their ratings, no matter how shallow their personal profit (Deterding, Dixon, Khaled, & Nacke, 2011). As usual in user forums, the majority of enrolled members in the electric vehicle forum are passive recipients. Also as is common, the composition of the forum changes over time. Some members leave, others members remain, and new members join. Following Dahlander and Frederiksen (2012), I chose to focus on the timespan of one year and obtained data from July 2014 to July 2015. To ensure the relevance of the exchange processes, I considered only discussions of technical issues. The forum has a chat section that allows members to communicate via personal messages, a practice that keeps the technical sections from going off-topic. Overall, 958 members contributed to a technical discussion within the study timespan. A norm in this community is that whenever a member directly addresses others, the member must indicate the reference by using the quote function. It is therefore transparent when members talk directly to one another. I was able to construct a network of interactions from this information. As a matter of rigor, I focused only on these unambiguous references and excluded posts that did not explicitly refer to other members. The members showed good compliance with the forum rules and used the quotation function in every third post (32.16%). The compliance rate was even higher for core members, who quoted in almost every other post (45.84%). Following Dahlander and

Frederiksen (2012), I used Borgatti and Everett's (2000) continuous core–periphery algorithm in UCINET and separated the interaction network into the core and its surrounding periphery. Overall, 50 members were part of the core, and 908 members belonged to the periphery.

Because I sought to explain the effects of core members' contact with the periphery on connectivity in the core, I focused exclusively on the evolution of the core network ( $N = 50$ ). The core–periphery distinction provided an empirically and theoretically meaningful boundary to this network. Aside from the content of their postings, I knew little about the core members, other than that all were male (which is in line with the composition of the overall population of this special interest forum), had been part of the community for an average of 4.28 years, and were located mostly in the United States (42%) and the European Union (14%). To avoid any bias resulting from missing information, I controlled for any unobserved time-invariant heterogeneity by using individual fixed effects in all regressions. I split the longitudinal one-year data into four periods of equal duration and constructed a panel data set, using quarterly information to balance the composition change. Although the activity of core members was very stable, 10 core members showed no activity in one or more periods. In the fixed effects regression models, I gave these joiners and leavers a value of 0, representing no activity in the respective period. I also used stochastic actor-oriented models based on the same panel data set. In line with Ripley, Snijders, Boda, Vörös, and Preciado (2015), I specified joiners and leavers as structural 0 values in the network models.

### 2.3.2. Empirical Approach

Other than the summary statistics in Table 1, I had no further information about forum members' individual characteristics. To deal with this lack of information about members' sociodemographic and psychological traits, I used individual fixed effects. The within-transformation,<sup>1</sup> also known as demeaning, allows for perfect control of unobserved time-invariant heterogeneity (Wooldridge, 2010). For the correct identification of the non-linear effect of contacts to the periphery on mindfulness postulated in H2b, I used fixed effects regressions with polynomial equations of the generalized form:

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<sup>1</sup> The fixed effects transformation controls for the time-invariant error term:  $(y_{ti} - \bar{y}_i) = \beta(x_{ti} - \bar{x}_i) + (\varepsilon_{ti} - \bar{\varepsilon}_i)$ .

$$E[\dot{y}_{it}|x_{it}] = \beta_1 \dot{x}_{it} + \beta_2 \dot{x}_{it}^2 + \beta_3 [\dot{x}_{it}^2 - \overline{\dot{x}_i^2}],$$

where  $\dot{x}_{it} = x_{it} - \bar{x}_i$  and  $\dot{x}_{it}^2 = x_{it}^2 - \bar{x}_i^2$ . This specification provides the opportunity to simultaneously model within and global non-linear effects (McIntosh & Schlenker, 2006). Technically, I used a hybrid model to estimate the time-varying effects together with the global effect (Allison, 2009). In addition to showing the main effect of members' contributions to the periphery on expert influence in the core, I was interested in investigating the underlying process. Thus, I employed tests for mediation with bootstrap confidence intervals to account for the mediation process proposed in H2 (Hayes, 2012). I furthermore aimed to rule out the inverse causality of the process. The rival explanation to H2 is that members with greater reach in the core can share more insights with the periphery. To test whether members' contributions to the periphery causally influence reach in the core, or vice versa, I specified actor-oriented network models. The model class of actor-oriented network models allows the separation of social selection from behavioral influence and enables clarification of the causality of the process (Steglich, Snijders, & Pearson, 2010). The models reflect the actor's satisfaction with the individual network environment. Actors try to improve their level of satisfaction with their positions over time. The means to this end are tie creation and termination. Members therefore constantly re-evaluate their positions within the core network and make decisions to resolve, maintain, or establish collaborations with peers. The network evaluation function of actor  $i$  is defined as (Ripley et al., 2015):

$$f_i^{net}(x) = \sum_k \beta_k^{net} s_{ik}^{net}(x).$$

The coefficients  $\beta_k^{net}$  represent the estimated relevance of the network effects  $s_{ik}^{net}$  to the actors' decisions with regard to improvements in the value of the objective function. Similarly, the behavioral evaluation function is defined as:

$$f_i^{beh}(x, z) = \sum_k \beta_k^{beh} s_{ik}^{beh}(x, z),$$

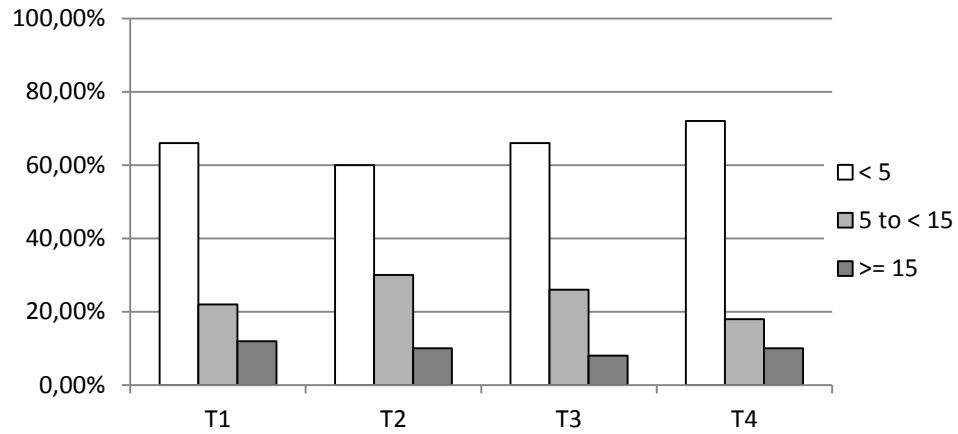
where  $z$  represents the behavioral dependent variable, and  $x$  is the dependent network variable (Ripley et al., 2015). In addition to including the mandatory behavioral shape effects in their linear and quadratic forms, I included the out-degree effect to investigate whether changes in the network influenced behavior dynamics and thus to clarify the causal direction of the process.

Whereas the panel regressions control perfectly for unobserved heterogeneity, the stochastic actor-oriented models take the social interdependence of members into account. Therefore, both approaches represent reciprocal robustness checks for the proposed relationship between core members' number of contributions to the periphery and their reach in the community core.

### **2.3.3. Measures**

*Number of Contributions to the Periphery.* I operationalized the number of contributions to the periphery by counting how many times a core member actively quoted a member from the periphery per period. As is usual for counts, the variable followed a Poisson distribution. Overall, 66 percent of the core members had less than five contributions to the periphery; 24 percent actively quoted peripheral members more than five but less than or equal to 15 times. Only 10 percent of the core members made more than 15 citations in any period. Although I used this variable in its continuous form in all panel regressions models, due to modeling requirements, I used an ordinal version organized according to three categories (low, middle, high) in the stochastic actor-oriented models (Snijders, van de Bunt & Steglich, 2010) (see Figure 3).

**Figure 3**  
Distribution of the Ordinal Version of  
Number of Contributions to the Periphery (Essay I)



*Mindfulness of Contribution Behavior in the Core:* I approximated the mindfulness of the contribution behavior in the core using the members reach in the core. Reach in the core served as a proxy for mindfulness, by capturing the amount of effort and attention that individuals allocated to interactions with peers in the core (Hargadon & Bechky, 2006). Reach in the core is a count of the unique peers a core member actively writes to within a period. I created a binary matrix of overt collaborations between core members in each period. Reach in the core thus equals the member's out-degree  $d_0(n_i)$ , that is, the number of nodes adjacent from  $n_i$  in the respective directed networks N1–N4 (Wasserman & Faust, 1994).

*Expert Influence in the Core.* I measured core members' expert influence in each period by applying the ExpertRank algorithm to the bipartite network of threads and posts. In online forums, ExpertRank—an algorithm similar to PageRank (Page, Brin, Motwani, & Winograd, 1999)—has the property of being a valid measure for members' expert knowledge (Zhang et al., 2007). The idea is that “if B is able to answer A's question, and C is able to answer B's question, C's expertise rank should be boosted not just because they were able to answer a question, but because they were able to answer a question of someone who herself had some expertise” (Zhang et al., 2007, p. 225). If core member A refers to posts from core member  $M_1 \dots M_n$ , the ExpertiseRank of member A is:

$$ER(A) = (1 - d) + d \left( \frac{ER(M_1)}{C(M_1)} + \dots + \frac{ER(M_n)}{C(M_n)} \right),$$

where  $C(M_1)$  is the number of core members assisting  $M_1$ . Similar to Zhang et al., I use the damping factor  $d = .85$  to let the random walker begin from different positions in  $(1 - d)$  percent of the cases. I used 100 iterations of the algorithm to calculate the values. Because I used a regression approach, I also rescaled the ExpertRank of each member by a factor of 100 to facilitate the interpretability of the fixed effects regression results based on deviations from one-unit changes.

## 2.4. Results

### 2.4.1. Descriptive Statistics

Tables 1 and 2 show the descriptive statistics reported in this section. I first report the descriptive statistics of the overall data set, reflecting the variation between the core members. The number of contributions to the periphery ( $M = 6.28$ ,  $SD = 10.80$ ) and reach in the core ( $M = 3.34$ ,  $SD = 3.30$ ) are count variables. Expert influence in the core ( $M = 15.20$ ,  $SD = 12.99$ ) has a minimum value of 0 and a maximum value of 61.50.

**Table 1**  
Summary Statistics of Variables (Between Variance) (Essay I)

Variable	Short Name	Mean	SD	Min	Max
Number of Contributions to the Periphery	(NRCONTPERI)	6.28	10.80	0.00	81.00
Reach in the Core	(REACHINCORE)	3.34	3.30	0.00	17.00
Expert Influence in the Core	(EXPERTIN)	15.20	12.99	0.00	61.50
Duration of Membership in Years		4.28	2.25	0.00	7.00
Location					
USA		0.42		0.00	1.00
EU		0.14		0.00	1.00
CANADA		0.10		0.00	1.00
AUSTRALIA		0.08		0.00	1.00
OTHER		0.04		0.00	1.00
N.N.		0.22		0.00	1.00

Notes: N = 50 x T = 4, N=200.

To account for the scarcity of information about core members, I used individual fixed effects in the regression analyses. Fixed effects models exclusively use individual deviations over time. Table 2 presents the descriptive statistics with regard to the within variance. Number of contributions to the periphery ( $M = 0.00$ ,  $SD = 5.95$ ) shows the greatest within variability, with an observed minimum of  $-30.75$  and a maximum of  $34.00$ .

**Table 2**  
Summary Statistics of Variables (Within Variance) (Essay I)

Variable	Mean	SD	Min	Max
NRCONTPERI	0.00	5.95	-30.75	34.00
REACHINCORE	0.00	2.23	-5.00	7.00
EXPERTIN	0.00	9.13	-22.50	31.60

*Notes:*  $N \times T = 200$  (for  $T = 4$  periods and  $N = 50$  members).

Table 3 shows the within correlation of all variables used in the fixed effects model. All correlations are statistically highly significant ( $p < 0.001$ ). Furthermore, all correlations have medium strength.

**Table 3**  
Correlation Matrix (Essay I)

	1.	2.
1. NRCONTPERI	-	
2. REACHINCORE	0.62***	-
3. EXPERTIN	0.34***	0.42***

*Notes*  $N = 200$ ; Table 3 shows the Pearson correlations between within-transformed variables; \*  $p < 0.05$ ; \*\*  $p < 0.01$ ; \*\*\*  $p < 0.001$ .



Table 4 shows the network density for the periods T1–T4. The average degree in all networks is 3.32. Density is low, indicating that collaborations between core members do not occur arbitrarily but are carefully chosen. This finding is affirmed in the network density that constantly decreases, from T1 (0.08) to T4 (0.05), and in the average degrees that decrease from T1 (4.10) to T4 (2.68). Degrees represent collaborations between actors. In comparison, the intensity of these interactions remains relatively stable across T1 (1.37), T2 (1.35), and T3 (1.36) and is somewhat lower only at T4 (1.19). There is a decrease in the number of collaborators, but members keep up the intensity of exchange with their remaining partners. Members therefore tend to become more selective in their collaborations over time.

**Table 4**  
Network Densities and Average Mindfulness per Period (Essay I)

Observation time	1.	2.	3.	4.
Density	0.08	0.07	0.06	0.05
Average degree	4.10	3.52	3.00	2.68
Number of ties	205	176	150	134
Average interaction intensity	1.37	1.35	1.36	1.19

*Notes:* N = 200.

Figure 3 presents the distribution of the categorized dependent behavioral variable, number of contributions to the periphery, as subsequently used in the stochastic actor-oriented models. Over time, most of the changes occur between the second and third category of this ordinal variable. Core members tend to change from Category 3 (more than 15 contacts with the periphery) to Category 2 (5–15 contacts with the periphery) over time; the share of members with less than 5 contacts to the periphery remains relatively stable. I observed only small changes between categories, one step at a time, as required (Ripley et al., 2015).

Overall, 58 percent of the core members change categories over time. To ensure that the periodically split network data are suitable for stochastic actor-oriented modeling, I calculated the Jaccard index

$$J = \frac{N_{11}}{N_{01} + N_{10} + N_{11}},$$

where  $N_{hk}$  is the number of tie variables with value  $h$  in one wave and value  $k$  in the next (see Table 5). The low  $J$  values (T1–T2 = 0.11, T2–T3 = 0.13, T3–T4 = 0.11) reflect the high turnover in the network between periods. It is empirically in line with the high levels of dynamics in online communities. Although  $J$  is low, it is not too low for the application of stochastic actor-oriented models. The average degrees decrease over time, so I expect satisfactory convergence of the models (Ripley et al., 2015).

**Table 5**  
Tie Changes between Periods (Essay I)

Period	0→1	1→0	1→1	Jaccard Index
T1 – T2	137	166	39	0.11
T2 – T3	113	139	37	0.13
T3 – T4	106	122	28	0.11

*Notes:* N = 50; Table 5 shows the transitions in the core relationships; (0)1 means (no) tie.

### 2.4.2. Hypotheses Tests

I used the panel data set with four waves and individual fixed effects to control for unobserved heterogeneity associated with the core members (see Table 6). All models were highly significant. With regard to the main effect (H1), I proposed that the more contacts a core member has with the periphery, the more the member's expert influence in the core increases. Model 1 accounts for 11 percent of the within variance between the change in the members' number of contributions to the periphery and change in their expert influence within the core ( $R^2 = .11$ ). The effect is positive and highly significant ( $b = .52, p < .001$ ), in support of H1. Model 2 shows that core members' expert influence is positively influenced by members' reach in the core ( $b = 1.73, p < .001$ ). The model accounts for 17 percent of the within variance in expert influence ( $R^2 = .17$ ). Model 3 tests H2, in which I proposed that there is a positive effect of the core member's contact with the periphery on the mindfulness of interactions, approximated via the members' reach in the core. Model 3 accounts for 38 percent of the within variance between the change in the number of contributions to the periphery and the change in the members' reach among peers in the core ( $R^2 = .38$ ). The effect is positive and highly significant ( $b = .23, p < .001$ ), in support of H2. To test the mediation hypothesis (H2), in which I proposed that core members' contributions to the periphery enhance their mindfulness and thus their expert influence, I specified Model 4. Model 4 ( $R^2 = .18$ ) includes reach as the proposed mediator variable. By comparing Models 1 and 4, I observed that the effect of members' number of contributions to the periphery was smaller in Model 4 ( $b = .19, p > .05$ ) and non-significant when I controlled for reach in the core ( $b = 1.41, p < .001$ ), in support of H2a. In Model 5, I tested the relationship between core members' number of contributions to the periphery and their reach in the core, which I expected to be inversely u-shaped (H2b), using a polynomial fixed effects regression. Model 5 therefore includes the squared term of the change in peripheral contribution behavior as well as the squared betweenness term thereof. This specification strategy is necessary for avoiding bias (McIntosh & Schlenker, 2006). Technically, Models 5 is an Allison hybrid model (Allison, 2009). The results of Model 5 shows that the positive linear within effect of peripheral contacts on reach in the core is highly significant ( $b = 0.41, p < .001$ ). The same applies to the squared within effect ( $b = 0.00, p < .001$ ) and the betweenness term thereof ( $b = -0.00, p < .001$ ). Only the member's betweenness term of number of contributions to the periphery has an inversely u-shaped effect on reach in the core ( $b = -0.00, p < .001$ ). The quadratic within term turned out to be positively u-

shaped instead. However, the parameter values of the quadratic effects are too small all together to warrant any meaningful interpretation. Hence, the within influence of mindfulness on the change in the number of collaborators is linear (M3), not quadratic. Therefore, H2b is not supported.

**Table 6**  
Fixed Effects Regression Models Showing the Influence of Members' Number of Contributions to the Periphery on Expert Influence and Reach in the Core (Essay I)

Dependent Variables									
EXPERTIN					REACHINCORE				
M1					M3				
	<i>Coeff.</i>	SE	<i>Coeff.</i>	SE	<i>Coeff.</i>	SE	<i>Coeff.</i>	SE	
NRCONTPERI	0.52***	(0.12)		0.19	(0.14)	0.23***	(0.02)	0.41***	(0.04)
NRCONTPERI <sup>2</sup>							0.00***	(0.00)	
B_NRCONTPERI <sup>2</sup>							-0.00***	(0.00)	
REACHINCORE			1.73***	(0.30)	1.41***	(0.38)			
Within R <sup>2</sup>	0.11		0.17		0.18		0.38		-

*Note:* N = 200; All models are specified using individual fixed effects perfectly controlling for unobserved heterogeneity; M5 is an Allison Hybrid model; B\_NRCONTPERI Member's absolute number of contacts to the periphery per period; \*p < 0.05; \*\*p < 0.01; \*\*\*p < 0.001.

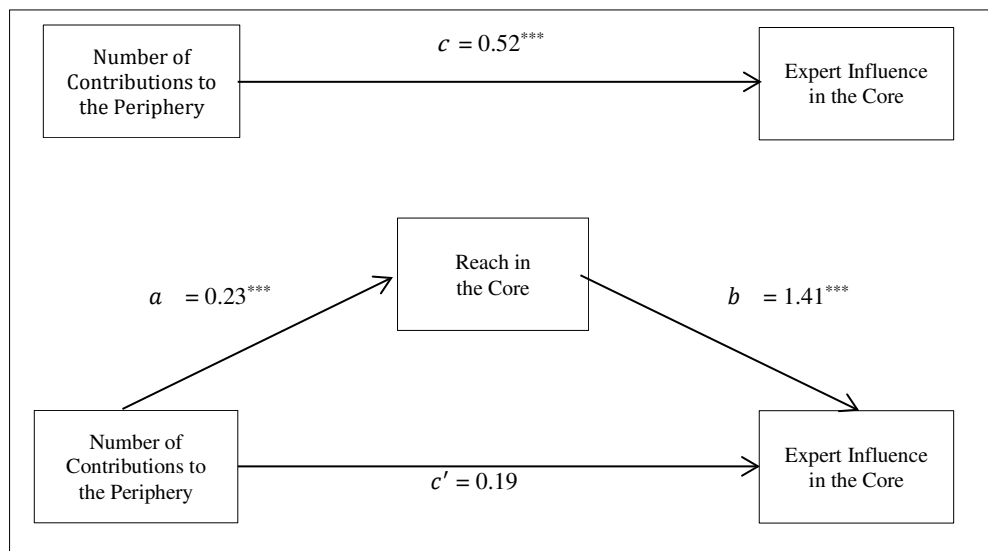
**Table 7**  
Mediation Analysis Testing the Mediated Influence of Members' Number of Contributions to the Periphery on Expert Influence (Essay I)

	Regression Coefficients			Indirect Effects		Bootstrap 95% Confidence Interval
	To EXPERTIN (EXP)	To REACHINCORE (RC)				
	<i>Coeff.</i>	<i>SE</i>	<i>Coeff</i>	<i>SE</i>	<i>Boot SE</i>	
NRCONTPERI (NCP)	0.19	(0.14)	0.23***	(0.02)		
REACHINCORE	1.41***	(0.38)				
Indirect Effect						
NCP – RC – EXP			0.33	(0.05)		0.10, 0.64

*Notes:* N = 200; All models are specified using individual fixed effects perfectly controlling for unobserved heterogeneity; EXP = Expert Influence; RC = Reach in the Core; NP = Number of Contributions to the Periphery; \* p < 0.05; \*\* p < 0.01; \*\*\* p < 0.001.

Following the recommendations of Hayes (2012), I investigated the causal influence process of core members' number of peripheral contacts on their reach in the core as well as on expert influence. Table 7 and figure 4 present the results of these mediation analyses. The direct effect, that is, the influence of members' number of contributions to the periphery on expert influence ( $b = 0.52, p < .001$ ), is supposed to be mediated by mindfulness, i.e. the proxy variable members' reach in the core. The indirect effect ( $b = 0.33, p < 0.05$ ) in the mediation model is significant when the more conservative bootstrap intervals are taken into account (LLCI 0.10, ULCI 0.64). In presence of the mediator, the direct effect of peripheral contacts on expert influence disappears ( $b = 0.19, p > 0.05$ ). The process between the members' number of contributions to the periphery and expert influence in the core is therefore fully mediated.

**Figure 4**  
Path Diagram of the Mediation Model (Essay I)



To establish causality and add robustness by accounting for the network structure of the data, I estimated social actor-oriented models. I applied the latest convergence criterion for RSiena with  $tmax$  smaller  $< 0.25$  and  $tconv.max \leq 0.10$ . All models achieved convergence. The results came from 3,000 iterations in sub-phase 4 of the algorithm (see Table 8). I checked the models for potential time heterogeneity and found consistency in the parameters across periods. All network and behavior rate parameter

values (M6–M8) were significant, showing that information from all waves (T1–T4) entered the parameter estimation. Network-rate parameter values can be further interpreted as the average number of core members' opportunities to decide whether to create, maintain, or terminate their relationships to other peers in the core. Because ties indicate that a member directly addressed a particular peer in the respective period, the decision to contact another member is made on the basis of receipt of content. Across all models, each member made a decision approximately every 25 posts.

Model 6 shows the social pattern of network change. The out-degree effect is negative ( $b = -1.97, p < .001$ ), such that core members do not arbitrarily communicate; they find collaborators in the core and establish repeated collaborations over time. The reciprocity effect is highly significant and positive ( $b = 1.85, p < .001$ ), such that members have a strong tendency to reciprocate contributions and engage in discussions with each other. The three-cycle effect also is positive and highly significant ( $b = 0.40, p < .001$ ), indicating that collaboration occurs in dense groups. However, the transitive reciprocal triplets effect is insignificant, suggesting that these groups are greater than three members ( $b = -0.09, p > .05$ ).

Model 7 is an extended version of Model 6; it accounts for behavioral influences in the network part of the model, controlling for behavior dynamics. Only the ego effect of the members' number of contributions to the periphery significantly influences network dynamics ( $b = 0.33, p < .01$ ). Therefore, the more contacts a core member creates with the periphery, the more the member's out-degree effect increases over time. In the behavioral part of the model, only the linear term is significant and negative ( $b = -1.30, p < .001$ ), showing that the tendency to create contacts with the periphery decreases over time. Model 8 also includes the out-degree effect from the network dynamics in the behavioral part of the model. Although the other effects, including the behavior ego effect ( $b = 0.34, p < .01$ ), stay almost the same between Models 7 and 8, the influence of core members' out-degree on their behavior dynamics is statistically insignificant ( $b = 0.17, p > .10$ ) in Model 8. Therefore, there is a significant effect of core members' number of contributions to the periphery on network dynamics (see Model 7), but no evidence of the inverse causal alternative.



**Table 8**  
Stochastic Actor-Oriented Models Showing the Causal Influence of Core Members' Number of Contributions to the Periphery on Reach in the Core (Essay I)

	M6		M7		M8	
Effect	<i>Coeff.</i>	SE	<i>Coeff.</i>	SE	<i>Coeff.</i>	SE
Network Dynamics						
Rate T1-T2	27.67***	(5.93)	48.87**	(16.61)	49.50*	(13.98)
Rate T2-T3	15.28***	(2.45)	22.58***	(4.58)	23.07***	(5.14)
Rate T3-T4	11.87***	(1.91)	21.21***	(4.88)	21.82***	(7.37)
Out-degree	-1.97***	(0.06)	-1.98***	(0.07)	-1.97***	(0.07)
Reciprocity	1.85***	(0.13)	1.86***	(0.14)	1.84***	(0.15)
Transitive Recipr. Triplets	-0.09	(0.07)	-0.09	(0.08)	-0.08	(0.08)
3-cycles	0.40***	(0.09)	0.35**	(0.09)	0.31**	(0.11)
NRCONTPERI alter			-0.07	(0.09)	-0.05	(0.10)
NRCONTPERI ego			0.33**	(0.10)	0.34**	(0.09)
NRCONTPERI similarity			-0.18	(0.20)	-0.18	(0.18)
Behavior Dynamics						
Rate T1-T2			1.22**	(0.47)	1.47*	(0.57)
Rate T2-T3			1.66**	(0.59)	2.24*	(1.10)
Rate T3-T4			1.56*	(0.57)	2.04*	(0.80)
NRCONTPERI linear shape			-1.30***	(0.29)	-1.67***	(0.35)
NRCONTPERI quadratic			0.59	(0.31)	0.14	(0.43)
NRCONTPERI out-degree					0.17	(0.11)

Notes: N = 50; \*p < 0.05; \*\*p < 0.01; \*\*\*p < 0.001.

## 2.5. Discussion

In this study, I investigate the benefits that accrue to core members who assist peripherals in online innovation communities. By using longitudinal data on the interactions between members of an online forum on building electric vehicles, I gather evidence that hints that core members increase their expert influence in the core when they assist members of the periphery. My results indicate that by answering questions from the periphery, core members increase their expert influence in the core over time (H1). I also determine the underlying process between assisting peripherals and having expert influence in the core. The greater the number of contributions that core members make to the periphery, the greater becomes the ability to contribute to peers in the core the core (H2) which ultimately leads to an increase in expert influence.

### 2.5.1. Theoretical Implications

This study contributes to core–periphery community interaction theory in three ways (Dahlander & Frederiksen, 2012; Rullani & Haefliger, 2013). First, it expands on the work of Dahlander and Frederiksen (2012) by showing why core members might have an incentive to become more involved in the core. Results indicate that core members can increase their expert influence among their peers over time by increasing their involvement with the periphery. This finding extends existing research by providing the counterpart to the explanation of how peripheral members profit from exchanging with the community core. Dahlander and Frederiksen (2012) find that by gradually coming closer to the core, peripherals increase their innovative performance, yet this effect tapers off, such that they reach the maximum of innovative performance even before becoming core members. Once a member is part of the core, the process comes to an end, and innovativeness can no longer increase. My study shows that the incentive for core members to assist peripheral members is that such assistance increases core members' influence in the core. Therefore, the relationship between the core and the periphery is symbiotic: Core members who become actively involved in discussions with peripheral members benefit from their efforts in terms of expert influence in the core.

Second, by revealing the benefits that an active exchange with the periphery yields to core members, I identify the micro foundations of the phenomenon that has been observed at the macro level. Researchers frequently argue that the entire community profits from exchange processes between the core and the periphery (Dahlander &

Frederiksen, 2012; Rullani & Haefliger, 2013). According to the logic of methodological individualism (Coleman, 1986), the relationship between core and periphery is a social macro-level explanation in need of a theoretical micro-level explanation. Research has shown that peripherals profit from exchanging with the core in terms of innovative performance (Dahlander & Frederiksen, 2012) and that members jointly develop social standards through collaboration that emerges in the core and propagates through the community (Rullani & Haefliger, 2013). Both previous findings attribute individual benefits to members of the periphery. My finding that core members benefit from actively engaging in discussions with peripherals is the missing piece of the micro-level puzzle. For core members, engaging with the periphery is not a waste of time. Just as peripheral members benefit in terms of innovative performance, core members profit in terms of expert influence among their peers. That is, mutual benefits at the micro (individual) level add up to macro (community) innovative performance.

Third, my study provides insights into core–periphery processes at the member level (Dahlander & Frederiksen, 2012) by identifying the process in which contacts with the periphery help core members improve their expert influence in the core. The periphery is the social sphere that produces the most radical ideas. Therefore, being involved in discussions in the periphery stimulates members in creative ways such that they can engage more mindfully with peers in the core. However, the circumstance that there is no evidence in support of hypothesis 2 b) suggests that there is not a clear optimum to this relationship. Furthermore, I show the causality of the process by using actor-oriented network models. Changes occurring in the members' reach within the core network are a consequence of their contribution behaviors related to the periphery: The more core members contribute to peripherals, the greater their ability to address others in the core. There is no evidence for the opposite causal explanation. Therefore, network changes are consequences, not antecedents, of core members' exchanges with the periphery.

### 2.5.2. Managerial Implications

The results of this study are relevant to innovation practitioners in three ways. First, when managers send invitations to co-creation workshops, they should focus on core members who are involved in vital exchanges with peripherals. Today, companies employ techniques such as netnography or social network analysis to find the right candidates for co-creation. Core members can be valuable partners for co-creation, because they have high levels of betweenness centrality and expert knowledge, two important facets of lead users (Kratzer et al., 2016). Practitioners can use the finding that contacts with the periphery increase the expert influence of core members as a criterion for deciding which experts to invite; members who have more contacts with the periphery, who contribute more mindfully in the core and increase their expert influence over time.

Second, it is a common open innovation practice to provide company hosted communities. On these platforms, members exchange their experiences with products and share their latest developments. My study shows that core members have an incentive to collaborate with peripheral members. This collaboration benefits both sides, so innovation managers can reinforce this mechanism to improve the overall innovative performance of their communities. Moderators could be employed to select intellectually stimulating questions from the periphery and present them to core members, tailored to their personal field of expertise, or contact the members by means of newsletters.

Third, when managers in offline settings need new insights, they should focus on experts who are in contact with peripheries. Although my study investigates periphery–core stimulation in the context of an innovative online community, I am confident that its findings also apply to offline communities of expertise. Online communities provide many social mechanisms that can be transferred to offline organizations (Faraj, Jarvenpaa, & Majchrzak, 2011). The setting of my investigation was an innovative online forum without gamification elements; core members' motivations to exchange with peripherals was therefore not biased by the star ratings or public lists that are frequently used in online settings to influence motivation. Because my results reflect the intrinsic motivation of core members to engage with peripherals, innovation managers can apply this study's findings in offline contexts such as co-creation workshops, conferences, or any settings in which experts deliberately exchange product ideas.

### 2.5.3. Limitations and Further Research

This study has three limitations. First, it examines the number of contributions a core member makes to peripheral members, without going into detail about the heterogeneity of peripheral members. Dahlander and Frederiksen (2012) infer such heterogeneity when they draw attention to the existence of *cosmopolitans*, members who are part of many online communities but participate only in the periphery, because they simply do not have the time to engage frequently in the community at hand. Because of their multiple memberships, they represent bridges between different communities. These bridging positions increase the creativity of cosmopolitans and make their ideas especially innovative. Another aspect that merits further research is the identification of peripherals who are lead users, a process that could be achieved using netnography. Because lead users are also highly innovative, core members may show a preference for assisting them.

Second, I chose to analyze an online forum that does not include ratings of the quality of contributions made by members; I aimed to study the pure social motivations of members to create contacts with the periphery, unbiased by potential gamification effects. However, gamification elements such as star ratings are a common phenomenon in many forums. Further research could focus on this interesting phenomenon to investigate a potential shift in motivation. Whereas in my study's setting, core members contribute to peripherals only when they gain an intellectual benefit from doing so, it is possible that gamification elements make core members contribute to cognitively less demanding or uninspiring topics, just to increase their scores. This behavior might corrupt the natural process among peripheral involvement, mindfulness, and expert influence in the core.

Third, this study focuses on a community with a socially defined core. I specified the core boundary using an algorithm (Borgatti & Everett, 2000) that Dahlander and Frederiksen (2012) applied in their article on the relationships of peripheral cosmopolitans to the core. Members who frequently interact are socially closer; they form the community core. However, there are many expert communities with cores that are defined by membership roles. According to Luhmann (2000), membership roles serve a dual purpose. The first membership role draws the community boundary and opens the possibility of differentiating further membership roles within an organization (Nassehi, 2005). In many forums, such as StackOverflow or the R-Community, core membership

is a formal role, and being part of the core is exclusive. In these contexts, core membership is an earned merit, not a direct measure of social proximity. Although most core members in these settings are frequent contributors, they do not have to remain active to retain their positions. For example, forum founders continue to belong to the cores of their communities even after they retire from active discussion. Researchers could examine these communities more closely and compare how results differ according to definition of the core as social (Borgatti & Everett, 2000; Dahlander & Frederiksen, 2012) or formal.

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### 3. Essay II:

## Launching Radical-Disruptive Innovations by Evening Out Inferior Performance Using Established Technology

Christian Nagel, Jan H. Schumann

*Radical-disruptive innovations (RDIs) represent unfamiliar technology and their performance is inferior to that of established products. From a managerial perspective, they are thus doubly difficult to market. Some companies try to even out their inferior performance by means of established technology (EIPET), such that they simultaneously introduce a modified version that includes an existing technology feature. Is EIPET an effective strategy for overcoming consumers' passive innovation resistance? Four data sources—scenario experiment, online survey of potential adopters of electric cars, actual field data on product usage in the post-adoption phase, and post-adoption survey of early adopters—provide evidence of a radical-disruptive innovation modification bias (RDIMB) in new product adoption. EIPET tempers the influence of passive resistance to innovation. Consumers express strong preferences for the functionally improved version due to their (1) need to insure against the risk of insufficient product performance, (2) overestimation of their true needs for the RDI, and (3) tendency to avoid search costs to evaluate potential alternatives. When consumers who do not need the added performance but purchase the modified version with the more expensive feature, they are not less satisfied and do not engage in negative word of mouth. The lack of negative consequences of EIPET indicates that managers can apply the strategy to increase adoption intentions among consumers who otherwise would defer their adoption decision and stick with the established technology.*

### 3.1. Introduction

When product development managers launch radical-disruptive innovations (RDIs), they sometimes adopt a strategy to counter consumer uncertainty: They address perceived shortcomings of the new products by simultaneously offering modified versions that include features of established technology. We refer to this marketing strategy as *evening out inferior performance using established technology* (EIPET). For example, because short driving range is a frequently perceived shortcoming of electric cars (Franke & Krems, 2013), BMW introduced its electric BMW i3 model in 2013 by simultaneously offering a more expensive version of the car that included a small combustion engine. The dual offering was designed to convince skeptical consumers of the new model's value.

Although many companies apply the EIPET strategy, there has not, to our knowledge, been any research that has described it or identified its underlying mechanisms and long-term consequences. This gap is surprising, given that product innovations that are both technologically innovative and designed to create new markets that (partially) substitute for existing markets (e.g., electric cars, e-book readers, voice over IP) have failure rates of 42 percent at product launch (Castellion & Markham, 2013). Such a high failure rate indicates the need to investigate the effectiveness and consequences of EIPET.

*Radical innovations*, that is, novel products produced by means of new technologies (Chandy & Tellis, 1998), evoke consumer uncertainty because they differ greatly from products with which consumers are familiar. *Disruptive innovations* exist in parallel to well-established products. At product launch, they underperform established products in mainstream markets (Christensen, 2016). Consumers tend to give them low ratings on the primary performance dimensions associated with established products. However, over time, disruptive innovations improve their ratings on primary dimensions, eventually catching up and appealing to the same consumers who initially despised them (Schmidt & Druehl, 2008). A major reason for new product failure is consumers' *passive innovation resistance* (Heidenreich & Spieth, 2013), that is, consumers' predisposition to cope with uncertainty by avoiding change. Such resistance prevents consumers from seriously considering and evaluating new products. Passive resistance is especially important in the context of product innovations that are radical and disruptive at the same time, because RDIs represent highly unfamiliar technologies that are

initially viewed as inferior to well-established alternatives. Research on constructive choice suggests that EIPET can be a viable strategy to reduce passive resistance. Consumers' uncertainty results from the incomparability of new and existing products, because of the radically new technology involved (Chaudhuri, Aboulnasr, & Ligas, 2010), and from the inferior performance of the disruptive offer compared with established alternatives (Christensen, 2016). Consumers therefore tend to postpone their adoption decisions. The attractiveness of an alternative depends on the characteristics of other options in the choice set (Bettman, Luce, & Payne, 1998; Huber, Payne, & Puto, 1982; Zhang & Zhang, 2007), so an EIPET strategy anticipates that in cases in which there is only one innovation of its kind, extending a consumer's choice set by offering a modified version with a significant performance surplus that uses established technology can generate artificial comparability.

Although product modification has been discussed as a means to improve innovation acceptance after product launch (Laukkanen, Sinkkonen, Kivijärvi, & Laukkanen, 2007; Ram, 1989), to the best of our knowledge, there has been no research on the consequences of making a functionally modified version available at the same time that an RDI is introduced to the market. Such research is important, because studies of radical innovations show that consumers have difficulty evaluating their true needs with regard to radically new products (Reinders, Frambach, & Schoormans, 2010). We suggest that these difficulties become even more severe when the radical innovation is also disruptive and consumers are limited to comparing it to established non-radical alternatives. In the case of electric cars, for example, consumers need less actual performance than they demand. Empirically, a driving range of about 80 kilometers is more than enough to cover consumers' daily driven distance for more than 80 percent of cases (Giffi, Vitale, Drew, Kuboshima, & Sase, 2011). However, those who are interested in purchasing electric cars express concerns about driving ranges that lead them to demand far more range than they actually need (Franke & Krems, 2013). Research on the concept of *flat-rate bias* shows there are situations in which customers are happy over the long term with seemingly irrational choices (Lambrecht & Skiera, 2006). We expect that customers' enduring need to avoid uncertainty prevents them from regretting their purchase decisions after opting for modified versions and investing large amounts of money in features they do not need. What has been demonstrated in the context of mobile tariff choices may also apply to RDIs such as electric cars. Our research addresses the following research questions:

- (1) Does EIPET weaken the influence of passive innovation resistance in consumers' decision processes?
- (2) How do consumers' ex post insights into their true needs influence their post-adoption behavior?

Using data from a scenario experiment, an online survey of potential adopters of electric cars, actual field data showing product usage in the post-adoption phase, and a post-adoption survey of early adopters, we find that the negative influence of passive innovation resistance on consumers' adoption intentions is significantly tempered when there is a functionally superior alternative added to the choice set. Our survey of potential purchasers of the BMW i3 reveals that customers' reasons for choosing a modified version are similar to customers' reasons for opting for a flat rate instead of a pay-per-use tariff (Lambrecht & Skiera, 2006). The field data show that customers of both versions of the innovation—modified and non-modified—do not differ with regard to post-adoption product usage. Our post-adoption survey reveals no negative long-term consequences of economically seemingly suboptimal purchase decisions: Neither less positive word of mouth (WOM), nor lower product satisfaction or attitude result when customers decide to purchase the modified version of a product but do not use the modification.

We contribute to theory on passive resistance to innovation (Heidenreich & Handrich, 2015; Heidenreich & Spieth, 2013; Ram, 1989) by identifying this EIPET marketing strategy. Altering consumers' choice sets is an effective means to overcome this passive resistance. Our findings also are relevant to the theory of disruptive innovation (Christensen, 2016), in that we identify the effects that drive consumers' preferences for modified versions of RDIs: overestimation, insurance, and convenience, as described by flat-rate bias research (Lambrecht & Skiera, 2006). We also identify a *radical-disruptive innovation modification bias* (RDIMB). This phenomenon results from the application of the EIPET strategy; it is comparable to the flat-rate bias phenomenon that arises in tariff-choice decision making (Lambrecht & Skiera, 2006). Our insights with regard to the consequences of EIPET are relevant to managers who wish to introduce RDIs to the market; we demonstrate that EIPET reduces passive resistance and increases new product success. Because consumers self-select RDI versions that best suit their psychological needs, there are no long-term negative consequences for WOM, attitude, or satisfaction when consumers opt for modified versions, even though the additional functionality is not objectively needed.



The next section provides a summary of the conceptual background of our study. We then present our hypotheses, describe our samples and method, and present the results of four empirical investigations. Next, we detail how our study contributes to theory and offer implications for innovation practitioners. Finally, we discuss some limitations and avenues for further research.

## 3.2. Theoretical Framework

### 3.2.1. Consumer Resistance to Innovation

Talke and Heidenreich (2014) argue that innovation research implicitly makes the assumption that consumers embrace new products. Traditional theories imply that consumers are intrinsically interested in exploring product innovations. According to the *diffusion of innovations* paradigm, consumers proceed through three pre-adoption phases, knowledge, persuasion, and decision making, before they adopt a product innovation (Rogers, 1995). However, as Talke and Heidenreich (2014) argue, even though knowledge about a product may be a prerequisite of convincing consumers, there is no guarantee of persuasion. Unless consumers have innovative personalities (Midgley & Dowling, 1978), they prefer to avoid novelty; the sensation of the new comes at the expense of the uncertain. Consumers seek to avoid uncertainty by refusing to engage in information processing and exhibiting immunity to the persuasion attempts of companies. This pattern is reflected in the high failure rates of innovations at product launch (Castellion & Markham, 2013). To reach out to potential customers who cannot be convinced with product-related information, companies need to account for consumer resistance (Ram, 1989; Ram & Sheth, 1989), or customers' perceived barriers to adopting the innovation. Consumers can be actively or passively resistant (Talke & Heidenreich, 2014). *Active resistance* refers to a conscious decision not to adopt an innovation; *passive resistance* refers to consumers' tendency to postpone the purchase decision about novel products to cope with uncertainty. To address the phenomenon of resistance to innovation, Ram (1989) suggests that rather than trying to persuade consumers, companies should directly modify the product innovation by using the strategy of innovation modification, that is, "altering the product concept to make it more acceptable to consumers" (p. 24). Especially in the context of durable consumer goods, product modification is an effective means to overcome consumer resistance (Ram, 1989).

### 3.2.2. Innovation Modification to Overcome Passive Resistance

Prior research has been limited to the phenomenon of sequential product modifications. Ram (1989) suggests that firms co-create product modifications with customers and then reintroduce the innovations as modified versions, which makes sense, given that consumers actively resist innovation. Active resistance results from unfavorable new product evaluations (Talke & Heidenreich, 2014). When consumers test products that fail to provide the necessary utility, firms must adjust their offers to meet customers' functionality requirements. The managerial reasoning behind EIPET differs somewhat from the purpose of sequential adjustments. By offering a modified version of an RDI with an additional feature that uses established technology, a firm may be able to address the perceived shortcomings of its innovation at product launch, meet the expectations of skeptical consumers, and address passive resistance. The approach is a managerial reaction to consumers' generic predisposition to resist innovation prior to new product evaluation (Talke & Heidenreich, 2014). By expanding portfolios or offerings with additional versions of innovations, firms enlarge the choice sets available to consumers. According to *rational choice theory*, consumers rely on a stable set of preferences when they choose among different options. However, according to the *theory of constructive preferences*, especially in situations of high uncertainty, consumer preferences are constructed rather than revealed (Bettman et al., 1998). Although consumers may have clear preferences for familiar products (Coupey, Irwin, & Payne, 1998), their choices of novel products can induce preferences for options that are superior on dominant attributes, especially as choice tasks get more complex (Bettman et al., 1998). The combination of unknown technology that is initially inferior to established alternatives with innovation that is radical and disruptive results in a high degree of consumer uncertainty. We argue that adding an option to the choice set that improves performance by using established technology is an appropriate way to reduce the influence of passive resistance on consumers' adoption intentions.

*H1: The addition of a functionally superior version of the RDI to a choice set weakens the negative influence of passive innovation resistance on consumers' adoption intentions.*

### 3.2.3. Consumers' Radical-Disruptive Innovation Modification Bias

Behavioral economists systematically examine biases in consumer behavior and study circumstances in which it deviates predictably from the behavior of rational, utility-maximizing people (Loewenstein, 2001). We anticipate significant parallels between the concept of EIPET to overcome consumers' passive resistance and the concept of a flat-rate bias (Lambrecht & Skiera, 2006). In customers' interactions with telecommunication service providers, flat-rate bias theory seeks to explain why consumers have a strong preference for tariffs with higher fixed fees and allowance instead that is not explained by usage volume. We propose that RDIMB is present in new product adoption. The first parallel between RDIMB and the flat-rate bias is that in both cases, companies simultaneously offer different versions of their products and services; consumers can choose between options that are sufficient to cover their true needs and at least one modified option that offers a significant surplus. The second parallel is that, in the post-purchase phase, consumers who opt for the modified option do not, in reality, need the surplus. There even may be a third parallel, in that there are no negative effects for companies in the long run, because customers are willing to pay for the psychological benefits they derive from modified options.

In the next section, we describe three causes of flat-rate bias—insurance, overestimation, and convenience effects—and explain their potential for causing RDIMB. A fourth cause refers to the taxi-meter effect that arises when “consumers enjoy their usage more on a flat rate than on a pay-per-use” basis (Lambrecht & Skiera, 2006, p. 213), because they do not have to “hear” the price tick upward during their consumption. Although flat rates decouple the pain of paying from the consumption of the modified alternative, technological modifications to RDIs offer additional surplus only in terms of performance. We thus do not consider the taxi-meter effect further, because it appears idiosyncratic to tariff choices.

***Insurance Effect.*** Consumers have difficulty evaluating their true needs with regard to radically new products (Reinders et al., 2010). They feel exposed to the risk that there is a gap between the true functional capability of innovations and the product performance promised by companies. However, consumers differ with regard to their levels of risk aversion. According to prospect theory, consumers have a binary taxonomy for the outcome of risky events (Kahneman & Tversky, 1979). Events can result

in losses or gains. Consumers are loss averse, such that losses have a greater impact on their utility function than gains of the same amount. In terms of product usage, a gain is a consumption experience free from difficulty, and a loss is a troublesome consumption experience. Because the utility gained from trouble-free consumption has a much smaller impact on consumers' utility function than the disutility derived from product-related complications, consumers want to insure themselves against the unlikely event of insufficient product performance during usage. Flat-rate bias researchers argue that consumer aversion to loss is one reason for the insurance effect (Lambrecht & Skiera, 2006). In a tariff-choice context, risk-averse consumers prefer a flat rate to prepare against the likelihood of having to pay extra at the end of the billing period (Miravete, 2003; Nunes, 2000). We argue that for consumers, just as flat rates act as insurance against the perceived risk of extra cost, additional product features supplied by means of established technology act as insurance against the perceived risk of poor performance.

*H2: Consumers' preference for purchasing RDI versions with additional features that even out the inferior performance of non-modified versions can be explained by the insurance effect.*

**Overestimation Effect.** Consumers may also find themselves in situations in which they truly overestimate their demand. By means of their radically new technology, RDIs make up a product class of their own; they have the potential to disrupt existing markets in which established products still exhibit superior performance (Chandy & Tellis, 1998; Christensen, 2016). However, according to Christensen (2016), firms can establish disruptive innovations successfully in the market, because—even though the innovations lag in performance—the new products are sufficient to meet consumers' needs. We argue that consumers use the superior performance of existing products as an anchor to derive estimates of their own needs in terms of the RDI (Kahneman, 1992). By using this unjustified reference point, consumers systematically overestimate their realistic needs related to the performance of the novel product; their preference for modified versions of RDIs results from overestimation of their true needs.

*H3: Consumers' preference for purchasing RDI versions with additional features that even out the inferior performance of non-modified versions can be explained by the overestimation effect.*

**Convenience Effect.** Unlike continuous innovations, radical innovations represent totally new technology (Chandy & Tellis, 1998). *Switching costs* arise as a side effect of this technological progress. When technology leapfrogs from one state to the other, consumers must keep up with the transition from old to new standards of technology. Burnham, Frels, and Mahajan (2003, p. 111) define economic risk costs as “the costs of accepting uncertainty with the potential negative outcome” when adopting a new product or service. *Learning costs* are switching costs that arise in the context of new product adoption decisions. To accept new technologies, consumers must comprehend the usefulness and ease of use of the technologies (Davis, 1989). They must invest time to learn about product advantages and develop the skills required to use the products (Burnham et al., 2003). Consumers also face evaluation costs, that is, “the time and effort costs associated with the search and analysis needed to make a switching decision” (Burnham et al., 2003, p. 111). By searching the market, consumers aim to maximize expected utility; they “search until the marginal expected cost of search becomes greater than its marginal expected return” (Nelson, 1970, p. 313). We argue that because of switching costs, marginal expected search costs are relatively high when consumers evaluate different products in a new market for a particular radical innovation. Bettman et al. (1998) show that consumers like simple choices and prefer dominant alternatives in choice sets. We argue that a convenient search strategy is to opt for the clearly dominant alternatives in choice sets, particularly among innovators and early adopters, who are usually of higher socioeconomic status than later cohorts in the diffusion process, so their greater wealth buffers the economic risk (Rogers, 1995). In other words, consumers’ preference for modified products results from the convenience effect.

*H4: Consumers’ preference for purchasing RDI versions with additional features that even out the inferior performance of non-modified versions can be explained by the convenience effect.*

### **3.2.4. Potential Effects of EIPET on Consumers' Attitudes and Behavior in the Post-Adoption Phase**

As previously noted, firms can introduce disruptive innovations to the market because, even if they may be somewhat inferior to established products, they are good enough to meet consumers' needs (Christensen, 2016). Therefore, consumers' ignorance about their true needs may result in unjustified comparisons to existing products. We expect that consumers who purchase RDI versions that include additional features with functional surpluses will not need the surpluses most of the time. Findings from flat-rate bias research suggest that because of the insurance effect, consumers can be happy in the long run with having chosen the functionally modified versions of RDIs, even though they pay extra to obtain them and do not use them in practice (Lambrecht & Skiera, 2006). Then for companies, there should be no negative effects in the long run.

*Propositions: Customers who adopt RDI versions with additional features that even out inferior performance (1) do not need them in the post-adoption phase, (2) are not less satisfied, (3) do not spread less positive word-of-mouth, (4) do not regret their purchase decisions, and (5) do not have a less positive attitude toward modified products than those who adopt non-modified products.*

### 3.3. Methods and Results

The focal product innovation for our research project is the BMW i3 electric car. It is ideal for investigating our research questions, because it is offered in two different versions that differ in just one product modification. All other aspects are constant between versions. That is, the modified version has a range extender, which is a small combustion engine developed to supply the driver with approximately 150 extra kilometers of driving range when needed. We provide an overview of all studies and hypotheses in Table 9.

**Table 9**  
Overview of Studies, Designs, Hypotheses, and Propositions (Essay II)

Study	Design	Hypotheses/Propositions	
1	Scenario Experiment	H1	The additional presence of a functionally superior version of the RDI to the choice set weakens the negative influence of passive resistance to innovation on the consumers' adoption intentions.
2	Representative Survey	H2	Consumer preference to purchase the version of an RDI with an additional feature that evens out the inferior performance of the non-modified version can be explained by the <b>insurance effect</b> .
		H3	Consumer preference to purchase the version of an RDI with an additional feature that evens out the inferior performance of the non-modified version can be explained by the <b>overestimation effect</b> .
		H4	Consumer preference to purchase the version of an RDI with an additional feature that evens out the inferior performance of the non-modified version can be explained by the <b>convenience effect</b> .
3	Field Data	P1	Purchasers who adopted the RDI with an additional feature that evens out inferior performance did not need it in the post-adoption phase.
4	Post-Adoption Survey	P2-5	Purchasers who adopted the RDI version with an additional feature that evens out inferior performance 2) were not less satisfied, 3) did not spread less positive word-of-mouth, 4) did not regret their purchase decisions, and 5) did not have a less positive attitude toward the product than those who adopted the non-modified version.



### 3.3.1. Study 1

**Study Design and Sample.** We conducted an online between-subjects scenario experiment among 319 potential customers of the BMW i3 electric car. We obtained our sample from a provider of online panels; it consisted of approximately equal shares of women (51%) and men (49%). The average age of the respondents was 47.67 years ( $SD = 14.33$ ), matching the typical age of purchasers of electric vehicles in Germany (Plötz, Schneider, Globisch, & Dütschke, 2014). To increase the external validity of the scenario experiment, our sample included only consumers with valid driving licenses. Because product adoption is a function of financial wealth (Rogers, 1995), and BMW i3 models are very expensive compared with ordinary cars of the same size, our sample also included only consumers with household net incomes above 2,400 euros per month. We present the descriptive statistics of Study 1 in Table 10.

**Table 10**  
Summary Statistics (Study 1) (Essay II)

	Mean	SD	Min	Max
Adoption Intention (ADOPTION)	0.39	-	0.00	1.00
Modification (MOD)	0.49	-	0.00	1.00
Passive Innovation Resistance (PIR)	3.39	0.50	1.76	4.92
Age	47.67	14.33	18.00	76.00
Education	0.33	-	0.00	1.00
Income	0.28	-	0.00	1.00

*Notes:* N = 319, Education = education dummy, where 1 is a graduate degree and 0 is no graduate degree; Income = income dummy, where 1 is household net income above 4000 Euros per month and 0 is below 4000 euros per month.

We randomly assigned respondents to one of two conditions. In the control condition, we presented participants with a brief description of the functional specifications of the BMW i3 electric car. After a manipulation check to ensure that the online respondents carefully processed the information, we asked “Can you imagine purchasing the BMW i3 within the next 5 years?” We offered two categories, “Yes, I can imagine purchasing the BMW i3 within the next 5 years,” and “No, I cannot imagine purchasing the BMW i3 anytime soon.” For participants assigned to the manipulation group, we also presented a description of the product specifications of the BMW i3 with a built-in range extender.

When these participants answered the question regarding their purchase intentions, they could also select the answer, “Yes, I can imagine purchasing the range extended version of the BMW i3 within the next 5 years,” with all other options the same.

**Measures.** We measured participants’ adoption intentions by observing their decision behavior. We assigned a value of 0 to the adoption intention variable when a participant decided not to consider adopting the BMW i3 within the next 5 years and assigned a value of 1 if the respondent indicated interest in adopting the electric vehicle. To measure participants’ passive innovation resistance, we used 11 items from Heidenreich and Handrich (2015), including reversed items to minimize the hazard of common method bias. We used a 6-point Likert scale, and consumers’ average passive innovation resistance in the sample was 3.39 ( $SD = 0.5$ ).

**Descriptive Results.** Table 11 shows the descriptive results of our choice experiment. In the control condition, 53 (33%) stated they could imagine purchasing the BMW i3 and 108 of 161 respondents (67%) opted to postpone their adoption choices. These results differed from results observed in the manipulated condition. Compared with the control condition, the share of participants that deferred the moment of adoption dropped from 67 percent to 54 percent. Demand shifted from the innovation without the additional feature, chosen by 15 participants (10%), to the version with the additional functional modification, selected by 57 participants (36%).

**Table 11**  
Descriptive Results of the Choice Experiment (Study 1) (Essay II)

Condition	Consumers' Choice						
	Without Feature		With Feature		Nothing		
	F	f	F	F	F	f	
1	53	0.33	-	-	108	0.67	161
2	15	0.10	57	0.36	86	0.54	158

Note: N = 319

**Hypothesis Tests.** To provide evidence for H1, we specified logistic regression models to predict respondents' adoption intentions shown in Table 12. We controlled for the effects of age, gender, education, and income. Model 2 includes an interaction term between passive innovation resistance and product modification ( $b = 0.98$ ,  $p < 0.05$ ), showing that the presence of the modification in the choice set tempered the influence of consumers' passive innovation resistance on adoption intentions. Therefore, H1 was supported.

**Table 12**  
Logistic Regressions Predicting: Adoption Intentions (Study 1) (Essay II)

DV: ADOPTION	M1		M2		M3		M4	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
MOD	0.55*	(0.23)	-2.73	(1.53)	0.67**	(0.25)	-1.17**	(0.38)
PIR	-0.49*	(0.21)	-1.07**	(0.36)	-0.57*	(0.22)	-2.80	(1.63)
PIR x MOD			0.98*	(0.47)			1.04*	(0.48)
Constant	0.92	(0.73)	2.86***	(1.20)	2.90***	(1.07)	4.92***	(1.49)
Individual Controls					Included		Included	
Observations	319		319		319		319	
Pseudo $R^2$	0.02		0.04		0.08		0.09	
Log-likelihood	-208.18		-205.70		-195.97		-193.54	

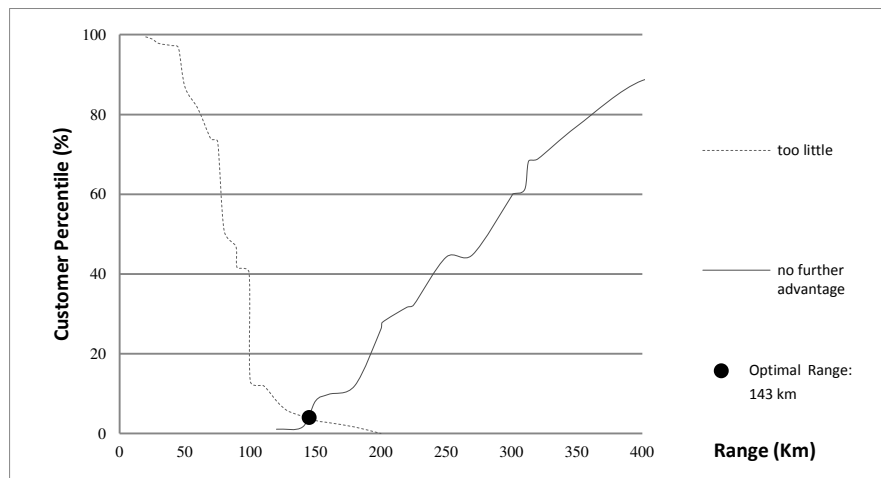
Note: Individual control variables are age, gender, and education.

### 3.3.2. Study 2

**Study Design and Sample.** In Study 2, we aimed to clarify why consumers prefer functionally modified but more expensive versions of product innovations. To provide externally valid results, we conducted a survey of a large sample that was representative of the population of potential purchasers of electric cars in Germany. We obtained our sample of 986 valid online surveys from a professional online panel provider. We presented our participants with a choice set that consisted of both versions of the BMW i3 electric car, that is, the innovation with and without the additional range extender. We used the actual technical specifications of both versions of the BMW i3 model and real prices. The functionally modified version exceeded the price of the basic version by 4500 euros. After the participants read the technical specifications, we asked them: “If you were to choose among both configurations of the BMW i3 electric car, which one would you buy?”

**Measures.** We assigned the model choice variable a value of 0 when a respondent opted for the electric car without the functional modification. We assigned a value of 1 if a participant indicated a preference for the more expensive car with the added range extender. We measured the four effects that cause flat-rate bias using the scales from Lambrecht and Skiera (2006), adapted to a product innovation context. Our measures were 6-point Likert scales ranging from “I totally disagree” to “I totally agree.” We measured the taxi-meter effect as an important covariate using three items from Lambrecht and Skiera (2006) ( $\alpha = 0.84$ ). For the convenience effect, we used an adapted 4-item scale that proved very reliable ( $\alpha = 0.86$ ). The insurance effect was a 2-item measure, and the items were strongly correlated ( $r(986) = .66, p < .001$ ). In line with Lambrecht and Skiera (2006), we used a combination of pre- and post-purchase data to operationalize the overestimation effect. We asked the participants from the pre-adoption study to indicate the ideal range for an electric car. We also used information from our post-adoption early adopter sample ( $N = 182$ ), as detailed in Study 4. By using a version of van Westendorp’s price sensitivity measure (van Westendorp, 1976) and adapting it to the electric mobility context, we obtained the optimal range of 143 kilometers for the BMW i3 electric car. Figure 5 shows these results: The overestimation effect is the delta between the consumers’ pre-adoption opinions regarding the ideal range and the optimal range determined through the van Westendorp method in the post-adoption survey.

**Figure 5**  
**Consumers' Optimal Range in the Post-Adoption Phase (Essay II)**



Note: Van Westendorp Price Sensitivity Measure Adapted to Determine Consumers' Optimal Range.

**Descriptive Statistics.** We present the descriptive statistics of the representative survey in Table 13; 79 percent of the respondents indicated they preferred the radical innovation with the functionally modified feature. Participants' overestimate of their true needs in terms of daily driving range was 201.81 km ( $M = 201.81$ ,  $SD = 289.93$ ), with 412 participants underestimating and 574 overestimating the empirically measured optimum (see Figure 5). We show the results of the correlation analysis in Table 14.

**Table 13**  
Summary Statistics (Study 2) (Essay II)

	Mean	SD	Min	Max
Preference for the modified version (CHOICE)	0.79	-	0.00	1.00
Insurance Effect (INSURANCE)	4.04	1.36	1.00	6.00
Taxi-Meter Effect (TAXI METER)	4.18	1.22	1.00	6.00
Convenience Effect (CONVENIENCE)	3.79	1.23	1.00	6.00
Overestimation Effect (OVERESTIMATION)	201.81	289.93	-40.0	2857.00
Age	44.5	14.26	18.00	69.00
Education	0.13	-	0.00	1.00
Income	0.37	-	0.00	1.00
Household Size	2.32	1.18	1.00	11.00
No. of Children in Household	0.40	0.77	0.00	7.00

*Note:* N = 986; The Income dummy variable separates households with a monthly net income below 2600 Euro (0) from those with a net income  $\geq$  2600 Euro (1).

**Table 14**  
Correlation Matrix (Study 2) (Essay II)

Variables	1.	2.	3.	4.
1. CHOICE	-			
2. INSURANCE	.22***	-		
3. TAXI METER	.23***	.60***	-	
4. CONVENIENCE	.21***	.22***	.48***	-
5. OVERESTIMATION	.21***	-.09**	-.02	.05

*Notes:* N = 986 correlations with CHOICE are point-biserial correlation coefficients,

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

**Hypothesis Test.** To explain consumers' preference for the modified version of the innovation, we estimated logistic regression models that predicted consumers' choices between the innovation with and without the functional feature (see Table 15). In model M5, three of four causes of the flat-rate bias significantly contributed to the prediction of consumers' preference for the version of the electric car with the functional feature. The insurance effect ( $b = .26, p < .01$ ), convenience effect ( $b = .22, p < .05$ ) and overestimation effect ( $b = .45, p < .001$ ) significantly predicted consumers' choices. With the controls for respondents' individual characteristics in Model 6, our results stayed consistent. Therefore, we find support for H2–H4.

**Table 15**  
Logistic Regressions Predicting: Consumers' Preference  
for the Modified Version (Study 2) (Essay II)

DV: CHOICE	M5		M6	
	<i>Coeff.</i>	SE	<i>Coeff.</i>	SE
INSURANCE	0.26**	(0.10)	0.33**	(0.10)
TAXI METER	0.14	(0.11)	0.14	(0.11)
CONVENIENCE	0.22*	(0.09)	0.22*	(0.09)
OVERESTIMATION	0.45***	(0.10)	0.47***	(0.11)
Constant	1.42***	(0.13)	1.74***	(0.28)
Individual Controls	Included			
<i>Observations</i>	986		986	
<i>Pseudo R<sup>2</sup></i>	0.06		0.08	
<i>Log-likelihood</i>	-478.96		-466.32	

*Notes:* Individual control variables included in M6 are comprised of consumer age, gender, education, income, household size, and number of children below 18 years living in the household; \*\*\* p < .001, \*\* p < .01, \* p < .05

### 3.3.3. Study 3

***Study Design and Sample.*** Study 3 was a field study that used data from actual purchasers of each version of the BMW i3 electric car, that is, the pure battery electric car and the electric car featuring a range extender. On the basis of a post-adoption survey of purchasers of the BMW i3 electric car, we selected a small subsample (N = 31) of respondents as representative of the population of early adopters. We provide the summary statistics in Table 16. The subsample consisted of equal shares of purchasers of the basic and modified products. Electronic sensors in the cars recorded customers' driving behavior for several months. We combined data from the field study and the post-adoption survey to model driving behavior with the necessary accuracy. We organized the data set hierarchically and nested the recorded driven distances (N = 40,096) within the subsample of drivers (N = 31).

**Table 16**  
Summary Statistics (Study 3) (Essay II)

	N	Mean	SD	Min	Max
Level 2					
Modification (MOD)	31	0.45		0.00	1.00
Age	31	51.26	8.60	24.00	73.00
Gender	31	0.06		0.00	1.00
Education	31	0.65		0.00	1.00
Income	31	0.26		0.00	1.00
Household Size	31	2.81	1.08	1.00	5.00
No. of Children in Household	31	0.68	0.75	0.00	2.00
Level 1					
Time since Adoption (TIME)	40092	13.36	3.60	4.00	22.00
No. of Trips on Given Day (NTRIPS)	40092	6.75	3.41	1.00	20.00
Distance in Km (DRIVENDISTANCE)	40092	11.88	17.39	0.10	231.92
Distance Driven in Countryside (DISTCO)	40092	29.40	29.08	0.00	100.00
Distance Driven on Highway (DISTHIGHW)	40092	6.99	19.05	0.00	98.84
Distance Driven in Town (DISTTOWN)	40092	63.61	32.55	0.00	100.00
Share of Trips per Day of the Week					
Monday	40092	0.15		0.00	1.00
Tuesday (TUESDAY)	40092	0.16		0.00	1.00
Wednesday (WEDNESDAY)	40092	0.14		0.00	1.00
Thursday (THURSDAY)	40092	0.15		0.00	1.00
Friday (FRIDAY)	40092	0.17		0.00	1.00
Saturday (SATURDAY)	40092	0.14		0.00	1.00
Sunday (SUNDAY)	40092	0.09		0.00	1.00

*Note:* Hierarchical data set with two levels. Variables belonging to the drivers are Level 2 and characteristics of the trips represent Level 1. The dummy variable Education shows that 65 percent of the participants are educated on the graduate level. The dummy variable Income is coded such that 26 percent of the participants have a household net income above 7.500 Euro.

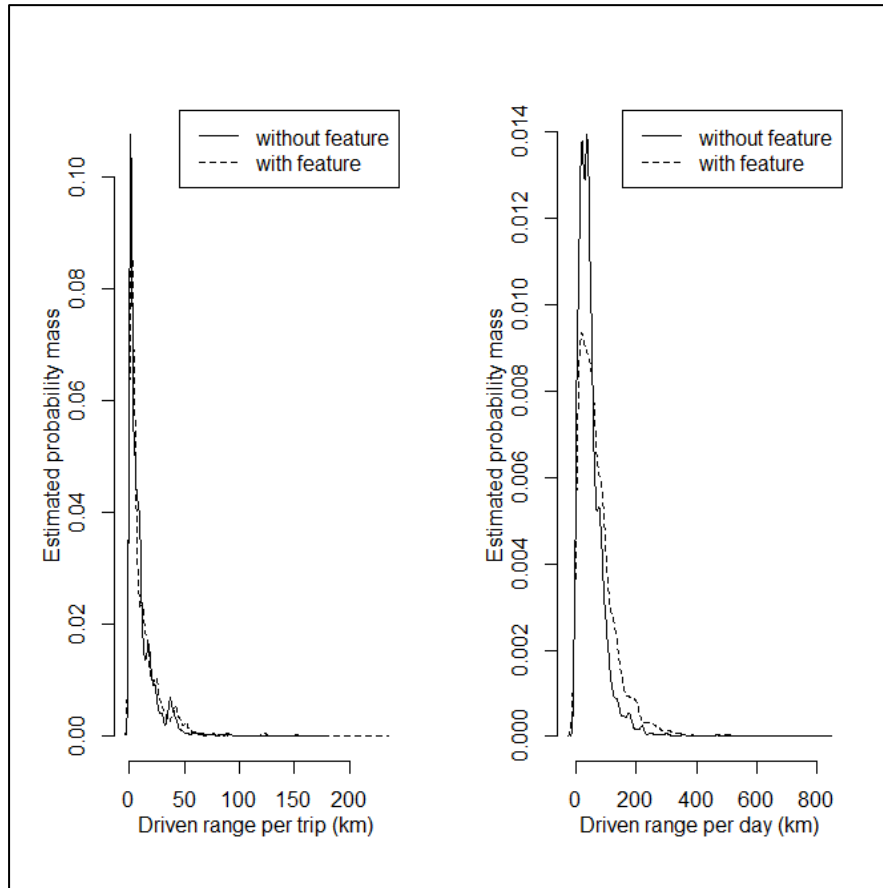


**Measures.** We measured behavioral data with built-in sensors in the electric cars. Driven distance was the sum of kilometers driven per trip. To control for differences in the driven distance resulting from situational factors, we also measured the shares of the distance driven in the countryside, in urban regions, and on highways. We also recorded days of the week, to adjust the model for different patterns of traffic volume. To control for different states of use diffusion (Shih & Venkatesh, 2004), we measured the number of months the purchaser had already adopted the car by calculating the difference between the particular date when a trip was recorded and the date of adoption.

**Descriptive Statistics.** We show smoothed density estimates of both groups in Figure 6. Although the adopters of the functionally modified electric car theoretically were able to drive farther distances, the density distributions of both groups were almost congruent. Purchasers of both versions were highly likely to drive short distances and equally unlikely to take trips that exceeded 50 kilometers.

**Figure 6**

Smoothed Density Estimates for Consumers' Driven Distances With and Without the Range-Extending Feature (Essay III)



*Notes:* The curves on the left side of Figure 6 show the smoothed density estimates for consumers' driven distances with and without the range-extending feature, per trip. The right side of Figure 6 illustrates the result of the data aggregated to driven distances per day.

We also calculated feature usage intensity. Customers on average made use of the range extender in 5 percent of their trips ( $M = 0.05$ ,  $SD = 0.05$ ). The median value of 0.04 showed that 50 percent of the customers did not use the range extender in 96 percent of their trips. We also aggregated the individual trips to driven distances per day ( $N = 8,036$ ). The right side of Figure 6 shows the smoothed density estimates on the aggregated data. The function corresponding to the version of the car without the range extender has more probability mass in the area below 100 kilometers than the version with the range extender. However, in the area of 100–200 kilometers of daily driven distance, the difference in probability masses between both versions of the innovation is small. Although purchasers with range extenders were likely to drive larger daily

distances, purchasers of the non-modified version also managed to drive large distances. We show the correlation matrices of study 3 in Tables 17 and 18.

**Table 17**  
Correlation Matrix (Driven Distance per Trip) (Study 3) (Essay II)

Variables	1.	2.	3.	4.	5.	6.
1. DRIVENDISTANCE	-					
2. TIME	-0.01	-				
3. NTRIPS	-0.15***	-0.03***	-			
4. DISTCO	0.19***	-0.05***	-0.06***	-		
5. DISTHIGHW	0.65***	-0.01**	-0.11***	-0.13***	-	
6. DISTTOWN	-0.55***	0.05***	-0.12***	-0.81***	-0.47***	-
7. MOD	0.07***	-0.19***	0.16***	0.13***	-0.02***	-0.10***

Notes: N = 40092, correlations with MODIFICATION are point-biserial correlation coefficients,  
\*\*\* p < .001, \*\* p < .01, \* p < .05.

**Table 18**  
Correlation Matrix (Driven Distance per Day) (Study 3) (Essay II)

Variables	1.	2.	3.	4.	5.	6.
1. DRIVENDISTANCE	-					
2. TIME	-0.02	-				
3. NTRIPS	-0.34***	0.00	-			
4. DISTCO	0.12***	-0.07***	-0.06***	-		
5. DISTHIGHW	0.45***	-0.01	-0.16***	-0.18***	-	
6. DISTTOWN	-0.39***	0.07***	0.16***	-0.77***	-0.49***	-
7. MOD	0.16***	-0.19***	0.14***	0.20***	-0.09***	-0.12***

Notes: N = 8036, correlations with MODIFICATION are point-biserial correlation coefficients,  
\*\*\* p < .001, \*\* p < .01, \* p < .05.

**Proposition Tests.** Because the variable daily driven distance was skewed to the right, we adjusted it by applying the natural logarithm when we used it as the dependent variable in our regression models. We show the regression results in Table 19. Models 7–14 are linear mixed models that account for the hierarchical structure of the data. Model 7 includes only the random intercepts and hence represents the null model. The conditional  $R^2$  of .10 indicates that there is a need to account for the multilevel structure.

Model 8 additionally includes the main predictor, that is, the binary variable modification. We found that purchasers of the more expensive modified version did not drive greater daily distances than those who adopted the radical innovation ( $b = 0.14, p > .05$ ). Model 9 contains the set of variables at level 1 as predictors to be used as control variables in Model 10. Model 10 includes the main predictor modification but also controls for individual differences in the number of trips, temporal influences, as well as the local context of the journey. We did not find, in any of the models, a significant difference with regard to driven distance between the modified and non-modified versions of the car ( $p > 0.05$ ). To test for robustness, we repeated the analysis on the basis of the aggregated data, using the log-transformed driven distance per day as the dependent variable in Models 11–14 (see Table 20). Model 11, again, is a null model with a conditional  $R^2$  of .21. Model 12 shows some influence of the modification on driven distance which is only marginally significant ( $b = 0.31, p > 0.10$ ) and disappears as soon as we properly control for other influences (M14). Our findings are in line with our previous analysis (M7-M10), in that we did not find a significant difference in driven distance per day between drivers of the basic and the modified electric vehicles on the 5 percent alpha significance level ( $p > 0.05$ ). Therefore, we accept our proposition 1.

**Table 19**  
Linear Multilevel Regression Models Predicting: log(Driven Distance per Trip) (Km)  
(Study 3) (Essay II)

Fixed Part	M7		M8		M9		M10	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
MOD			0.14	0.17			0.00	0.13
TIME					-0.00	0.00	-0.00	0.00
NTRIPS					-0.04 <sup>***</sup>	0.00	-0.04 <sup>***</sup>	0.00
DISTCO					0.03 <sup>***</sup>	0.00	0.03 <sup>***</sup>	0.00
DISTHIGHW					0.04 <sup>***</sup>	0.00	0.04 <sup>***</sup>	0.00
TUESDAY					0.03	0.02	0.03	0.02
WEDNESDAY					0.06 <sup>***</sup>	0.02	0.06 <sup>***</sup>	0.02
THURSDAY					0.03	0.02	0.03	0.02
FRIDAY					0.04 <sup>*</sup>	0.02	0.04 <sup>*</sup>	0.02
SATURDAY					-0.03	0.02	-0.03	0.02
SUNDAY					-0.01	0.02	-0.01	0.02
Intercept	1.62 <sup>***</sup>	0.08	1.56 <sup>***</sup>	0.12	0.67 <sup>***</sup>	0.07	0.67 <sup>***</sup>	0.07
Random Part	Var	$\sigma^2$	Var	$\sigma^2$	Var	$\sigma^2$	Var	$\sigma^2$
Intercept	0.22	0.47	0.22	0.47	0.12	0.35	0.13	0.36
Residuals	1.86	1.36	1.86	1.36	0.83	0.91	0.83	0.91
Observations	40092		40092		40092		40092	
Marginal $R^2$	0.00		0.00		0.58		0.58	
Conditional $R^2$	0.10		0.11		0.64		0.64	

Note: All models were fit using Restricted Maximum Likelihood. <sup>\*\*\*</sup>  $p < .001$ , <sup>\*\*</sup>  $p < .01$ , <sup>\*</sup>  $p < .05$

**Table 20**  
Linear Multilevel Regression Models Predicting: log(Driven Distance per Day) (Km)  
(Study 3) (Essay II)

	M11		M12		M13		M14	
Fixed Part	<i>Coeff.</i>	<i>SE</i>	<i>Coeff.</i>	<i>SE</i>	<i>Coeff.</i>	<i>SE</i>	<i>Coeff.</i>	<i>SE</i>
MOD			0.31	0.19			0.10	0.13
TIME					0.00	0.00	0.00	0.00
NTRIPS					0.21***	0.00	0.21***	0.00
DISTCO					0.03***	0.00	0.03***	0.00
DISTHIGHW					0.04***	0.00	0.04***	0.00
TUESDAY					0.04	0.03	0.04	0.03
WEDNESDAY					0.08**	0.03	0.08**	0.03
THURSDAY					0.04	0.03	0.04	0.03
FRIDAY					0.09**	0.03	0.09**	0.03
SATURDAY					0.00	0.03	0.00	0.03
SUNDAY					-0.06*	0.03	-0.06*	0.03
Intercept	3.59***	0.09	3.44***	0.12	1.38***	0.08	1.38***	0.08
Random Part	Var	$\sigma^2$	Var	$\sigma^2$	Var	$\sigma^2$	Var	$\sigma^2$
Intercept	0.27	0.52	0.26	0.51	0.14	0.37	0.14	0.38
Residuals	1.00	1.00	1.00	1.00	0.46	0.68	0.47	0.68
Observations	8036		8036		8036		8036	
Marginal $R^2$	0.00		0.02		0.58		0.58	
Conditional $R^2$	0.21		0.22		0.68		0.68	

*Note:* All models were fit using Restricted Maximum Likelihood. \*\*\*  $p < .001$ , \*\*  $p < .01$ , \*  $p < .05$

### 3.3.4. Study 4

**Study Design and Sample.** Study 4 was a post-adoption survey of early adopters of both versions of the BMW i3 electric car. The sample consisted of 182 purchasers of the car. Respondents answered questions regarding their product satisfaction, attitude towards the innovation, and positive WOM behavior.

**Measures.** We asked respondents to indicate which type of BMW i3 they owned. If they owned the modified version, we asked them specific questions about the range extender to confirm the plausibility of the information they provided. We measured customer attitude toward the product with 5 items from Tybout et al. (2005). The scale showed good reliability ( $\alpha = 0.79$ ). To measure customer satisfaction, we used 10 items adapted from Brown, Barry, Dacin and Gunst (2005). The measure showed good reliability ( $\alpha = .78$ ) as well. We measured customer regret of the purchase decision using 3 items from Inman and Zeelenberg (2002). The measurement was highly reliable ( $\alpha = .90$ ). We measured positive WOM with 2 items from Arnett, German, and Hunt (2003), which were positively correlated ( $r(182) = .65, p < .001$ ).

**Descriptive Statistics.** Our descriptive results (see Table 21) show that customers were very satisfied with their electric cars in the post-adoption phase: The customer satisfaction scale (a 7-point Likert scale) had a mean value of 5.84 (SD = 0.57). We also measured customer attitude toward the product (M = 5.38, SD = 0.56), customer regret about the purchase decision (M = 1.25, SD = 0.69), and positive WOM (M = 5.57, SD = 0.67), on 6-point Likert scales. Because of purchasers' overall positive evaluations of the product and their purchase decisions, the observed distributions of the variables strongly deviated from the normal distribution shape. To prepare for the hypotheses tests, we therefore categorized the data. We split the customer satisfaction and attitude toward the product variables at their median values, into low (0) and high (1) categories. The variables for post-purchase regret and positive WOM exhibited stronger skew, so we focused on the poles of the scales for the transformation procedure. The categorical regret variable was 0 ( $n = 143$ ) when customers did not regret their purchase decision at all (equal to 1 at the arithmetic index) and 1 ( $n = 39$ ) when customers reported feeling regret. The categorical version of positive WOM was 1 ( $n = 110$ ) when customers strongly recommended the product to their peers and 0 ( $n = 72$ ) otherwise. We show the correlation matrix of study 4 in Table 22.

**Table 21**  
Summary Statistics (Study 4) (Essay II)

	Mean	SD	Min	Max
Modification (MOD)	0.36	-	0.00	1.00
Product Attitude (ATTITUDE)	5.38	0.56	3.40	6.00
Product Satisfaction (PSATIS)	5.84	0.57	3.20	6.90
Positive Word-of-Mouth (PWOM)	5.57	0.67	3.00	6.00
Post-Purchase Regret (REGRET)	1.25	0.69	1.00	5.33
Age	53.03	9.38	27.00	80.00
Gender	0.08	-	0.00	1.00
Education	0.63	-	0.00	1.00
Income	0.31	-	0.00	1.00
Household Size	2.81	1.26	1.00	7.00
No. of Children in Household	0.68	0.98	0.00	5.00

*Note:* N = 182

**Table 22**  
Correlation Matrix (Study 4) (Essay II)

Variables	1.	2.	3.	4.
1. MOD	-			
2. ATTITUDE	-.07	-		
3. SATIS	-.01	.59***	-	
4. REGRET	-.12	-.34***	-.45***	
5. PWOM	-.02	.47***	.42***	-.52***

*Notes:* N = 182 correlations with MODIFICATION are point-biserial correlation coefficients, \*\*\* p < .001, \*\* p < .01, \* p < .05.



***Proposition Tests.*** To test Proposition 6, we estimated a series of logistic regression models as shown in Table 23. We did not find a significant difference between customers of the two versions with regard to their post-adoption attitudes (M15–M16). The influence of modification on satisfaction was also insignificant (M17–M18). Furthermore, there was no significant influence of having bought the feature on post-purchase regret (M19–M20). Moreover, customers who purchased the modified version did not spread significantly less WOM among their peers (M21–M22). We therefore accepted Propositions 2–5.

**Table 23**  
Logistic Regressions Predicting: Attitude to the Innovation, Product Satisfaction, Post-Purchase Regret and Positive Word-of-Mouth (Study 4) (Essay II)

DV:	ATTITUDE			SATIS			REGRET			PWOM		
	M15	M16	M17	M18	M19	M20	M21	M22				
	<i>Coeff.</i>	<i>SE</i>	<i>Coeff.</i>	<i>SE</i>	<i>Coeff.</i>	<i>SE</i>	<i>Coeff.</i>	<i>SE</i>	<i>Coeff.</i>	<i>SE</i>	<i>Coeff.</i>	<i>SE</i>
MODIFICATION	-0.07 (0.30)	-0.12 (0.31)	-0.02 (0.31)	-0.02 (0.32)	-0.16 (0.38)	-0.13 (0.38)	0.01 (0.31)	-0.04 (0.32)				
Constant	-0.10 (0.18)	-1.31 (1.09)	0.27 (0.18)	-1.12 (1.12)	-1.24 (0.22)	0.27 (1.30)	0.41 (0.18)	-0.55 (1.11)				
Individual Controls	Included			Included			Included					
Observations	182	182	182	182	182	182	182	182				
Pseudo R <sup>2</sup>	0.00	0.02	0.00	0.03	0.00	0.04	0.00	0.03				
Log-likelihood	-0.01	-123.67	-0.01	-120.20	-94.47	-90.99	-12.21	-118.44				

*Notes:* Individual control variables included in M16, M18, M20 and M22 are comprised of consumer age, gender, education, income, household size, and number of children below 18 years living in the household. \*\*\*  $p < .001$ , \*\*  $p < .01$ , \*  $p < .05$ .

## 3.4. General Discussion

### 3.4.1. Theoretical Implications

Our study offers three key implications to the emerging theory of consumer resistance to innovation (Talke & Heidenreich, 2014). First, we contribute to theory on innovation resistance (Heidenreich & Handrich, 2015; Heidenreich & Spieth, 2013; Ram, 1989) by identifying the relevant marketing strategy of EIPET. We show that EIPET weakens the influence of passive resistance to consumers' adoption intentions. By introducing a clearly dominant alternative to a consumers' choice set (Bettman et al., 1998), we were able to nudge passively resistant consumers to consider product adoption in the near future; EIPET thus appears to offer an effective remedy for passive innovation resistance (Heidenreich & Handrich, 2015). Our finding illustrates that because of consumer irrationality (Bagozzi & Lee, 1999), product adoption is a context in which the principles of choice architecture can be employed (Thaler & Sunstein, 2008) to discover systematic deviations from rational decision making and improve understanding of adoption decisions.

Second, by using mental accounting theory (Kahneman, 1992; Kahneman & Tversky, 1979), we provide a deeper understanding of the underlying reasons for the success of EIPET. We draw analogies to flat-rate bias research (Lambrecht & Skiera, 2006) and show that the insurance effect and the overestimation effect apply to the RDI adoption context just as they do to the tariff-choice setting. However, the contexts differ with regard to the convenience effect. The convenience effect has not been confirmed in the tariff-choice setting; it arises only in the product adoption context. We argue that switching costs (i.e., economic risk, learning, and evaluation costs) likely are higher when consumers confront RDIs rather than alternative tariffs that are horizontally comparable. Consumers' tendency to stick with their anchor in terms of performance explains their preference for a radically innovative product that offers (almost) the level of performance to which they are accustomed.

Third, in delineating the parallels between the strategy of offering flat rates and EIPET in innovation adoption, we contribute to theory on RDIs (Chandy & Tellis, 1998; Christensen, 2016) by identifying the RDIMB. The application of EIPET results in outcomes with remarkable parallels to the behavioral consequences of flat-rate bias (Lam-

brecht & Skiera, 2006). In both cases, companies introduce a further option to the consumers' choice set that is functionally superior, and that addition, in terms of functionality, is not actually needed. Consumers did not really need the extra feature of the electric car to drive greater distances. Their preference for the added feature stems from their need for insurance, so the feature remains a psychological means to an end, even if it is rarely used, and consumers could do without it. In cases of both EIPET and flat-rate bias, consumers seem happy with their choices, such that their product usage experience with modified versions does not negatively affect their attitudes toward products, satisfaction with products, feelings about purchase decisions, or WOM in the post-adoption phase.

### **3.4.2. Managerial Implications**

Our study offers three important managerial implications. First, it suggests that when introducing RDIs, managers should enlarge consumers' choice sets with functionally superior modified versions by using established technology to increase the adoption intentions of those consumers who would otherwise defer their choices and stick with default versions. We show that EIPET is an effective way to address consumers' passive resistance. Managers invest vast amounts of money in research and development to build the technological foundations of radical innovations; it is relatively cheap to offer a functional surplus by adding an established technology feature to a product. Although engineering such a feature increases total development costs, it results in greater market share at product launch and ultimately benefits overall sales, because the breadth of the diffusion of novel products depends on the size of the innovator- and early-adopter cohorts (Rogers, 1995).

Second, managers should allocate a significant share of their overall production capacity to producing RDI versions with additional functional features. During production planning, managers should acknowledge that consumers prefer modified versions of RDIs. Our descriptive findings show a demand shift from the radical innovation to its functionally superior, modified counterpart.

Third, managers who apply EIPET can count on RDIMB in the long run; there do not seem to be any rebound effects from consumers' post-adoption experiences. Even though, objectively, consumers do not need the functional surpluses associated with modified products, they are not less satisfied with the modified products. By offering

modified products along with non-modified radical innovations, managers can increase consumers' abilities to self-select the alternatives that best fit their psychological needs of insurance and convenience. Therefore, EIPET grants mutual benefits to firms (increase in consumers' adoption intentions) and consumers (products that suit their long-term needs).

### **3.4.3. Limitations and Further Research**

Our study has some limitations that suggest avenues for further research. We investigated a functionally modified feature that added a surplus to a radical innovation using established technology. Our focal RDI was an electric vehicle, and the additional feature was a range extender, a small combustion engine that works like an emergency backup generator when needed. Further research could investigate whether a modification bias arises when the focal innovation is not disruptive, that is, not inferior to existing products, and radical only in that it represents totally new technology. The convenience effect, consumers' limited willingness to search the market and select familiar options, is a hint that products that disguise radical innovations as continuous innovations (by adding features from familiar technology) may also increase adoption intentions. Thus, by using experimental conditions, researchers could investigate the effect that results from reframing radical innovations as continuous innovations.

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## 4. Essay III:

### **Post-Adoption Halo Effects of Aesthetic Product Evaluations and the Moderating Role of Innate Consumer Innovativeness**

Christian Nagel, Jan H. Schumann

*Aesthetic product appearances can create halo effects in the pre-adoption phase that lead consumers to base their expectations on the aesthetics rather than on objective information about innovative products. Does this halo effect of perceived aesthetic value persist in the post-adoption phase, or does it instead become a rebound effect? Using longitudinal post-adoption data from early adopters of an electric car model, this study shows that consumers' perceptions of aesthetic value buffer the effect of product-related hedonic and functional experience on attitudes toward the product. The more value consumers derive from product aesthetics over time, the less they ground their attitudes on actual hedonic or functional experience. Product managers thus should opt for designs that grant aesthetic pleasure over time. Innate consumer innovativeness levels moderate the buffering effect, such that the halo effect of aesthetic product evaluations on the relationship between experienced hedonic utility and attitude only exists for highly innovative consumers. Innovative consumers are especially sensitive to aesthetic value, so in their co-creation efforts, managers should seek out these customers, because doing so can increase early adopters' long-term product satisfaction and word of mouth, both of which expand the breadth of diffusion for the innovations.*

## 4.1. Introduction

To market innovations, ensuring sufficient utility for early adopters is a crucial goal. Research highlights the need to meet customers' expectations regarding product usefulness and relative advantage (Rogers, 1995; Venkatesh, Thong, & Xu, 2012), especially in relation to innovative products, because the decision to adopt or reject such products features high levels of uncertainty and the risk of the unknown. To convince consumers of the utility of novel products, aesthetic value often is even more relevant than objective information, because visual cues provide reliable information, in that they represent a direct form of experience, using the consumer's own senses. Therefore, managers leverage their innovative products' appearance to create halo effects in the pre-adoption phase and reduce the relevance of objective, product-related information (Hoegg & Alba, 2011).

Although knowledge about adoption intentions and decisions is broad and deep, insights into consumer perceptions in the post-adoption phase are notably scarce (Rogers, 1995), likely due to data accessibility limitations. That is, we know that an aesthetic impression increases purchase intentions (Truong, Klink, Fort-Rioche, & Athaide, 2014), but we do not know the extent to which this influence affects consumer behavior after the product has been adopted. From a pessimistic perspective, there might be no long-term halo effect of product aesthetics, because actual post-adoption usage experiences could replace aesthetic cues as relevant indicators of products' advantages. In this case, the initial halo effect even might backfire after the adoption phase, such as if exaggerated, design-induced expectations fail to match the actual experienced utility (Churchill & Surprenant, 1982). There also is some reason to be more optimistic though. Research shows that product design informs customer satisfaction in the post-adoption phase (Chitturi, Raghunathan, & Mahajan, 2008), such that managers still might count on a halo effect of product aesthetics in the post-adoption phase.

Midgley and Dowling (1978) reason that a substantial share of early adopters are *innovative consumers*. Consumer innovativeness is a personality trait that causes people to seek out the new and different (Hirschman, 1980). When innate consumer innovativeness exerts a moderating effect, marketing managers likely can optimize product aesthetics to meet the long-term preferences of innovative consumers and thus improve attitudes toward product innovations among a substantial segment of early adopters. Building on this prior research into the halo effect in innovation marketing

(Hoegg & Alba, 2011) and the influences of consumer innovativeness (Bartels & Reinders, 2011; Midgley & Dowling, 1978), we address two research questions:

- (1) Is there a halo effect of perceived aesthetic value, buffering between product experience and attitude in the post-adoption phase?
- (2) Does the potential halo effect vary in strength according to consumers' level of innate innovativeness?

To address these questions, we build on two ideas. First, similar to the influence of aesthetics in the pre-adoption period, a post-adoption halo effect might reduce the relevance of objective information for product evaluations. In a post-adoption context, the central objective information is consumers' first-hand experience with innovations' hedonic and functional performance. When consumers derive more aesthetic value from innovative products over time, it might reduce the relevance of their product experience in determining their product attitudes in the long term. Second, Truong et al. (2014), in considering a derivative of the more general consumer innovativeness trait, show that innovative consumers' adoption intentions are linked to their perceptions of the aesthetic appearance of the focal innovation. Thus, consumer innovativeness seemingly might moderate the halo effect in the post-adoption phase.

As our theoretical contribution, we seek to clarify the interplay among perceived aesthetic value, hedonic and functional product experience, and product attitudes in the innovation post-adoption phase. We predict that perceived aesthetic value exerts a buffering halo effect on the relationship between product experience and attitude; we also note the role of innate consumer innovativeness in this context. Innate consumer innovativeness should strengthen the buffering post-adoption halo effect of product aesthetics on hedonic experience but weaken it in relation to functional experience. In turn, managers might leverage aesthetic value to increase purchase intentions, as well as to buffer the relevance of post-adoption product experience over time. When targeting innovative consumers, they can effectively rely on long-term product fun, via aesthetic value, though they also must be careful to provide long-term functional performance.

With a longitudinal survey of early adopters of the BMW i3 electric car, we find general support for our predictions. According to the fixed effects panel regressions, perceived aesthetic value creates a halo effect in the post-adoption phase, buffering the effect of consumers' hedonic and functional usage experience on attitudes toward the product. A three-way interaction model further reveals that consumers with high levels

of innate innovativeness are especially sensitive to long-term perceptions of aesthetic value, resulting in a stronger buffering effect for their experience of product fun. However, we do not find a weaker effect of consumer innovativeness related to the influence of functional experience.

After providing the conceptual background for our study, we derive hypotheses and illustrate the conceptual framework, as detailed in Figure 7. We then explain the sample and applied methods. Furthermore, we detail how this study contributes to theory while also offering important implications for innovation practitioners. We finally discuss the limitations of this study and suggest some directions for further research.

## **4.2. Theoretical Framework**

### **4.2.1. Relevance of Product Aesthetics**

The diffusion of innovations paradigm (Rogers, 1995) and technology acceptance model (Venkatesh et al., 2012) focus on the properties of novel products. Both traditions argue that an innovation must be perceived as useful, easy to learn, and relatively advantageous (Rogers, 1995; Venkatesh et al., 2012). Before adoption, consumers rarely have opportunities to test the product though, so they instead rely on visual cues to make their product judgments, because appearance offers an initial experience of the product, according to one's own senses (Chitturi et al., 2008). Consumers rely on visual cues to infer usefulness, fun, or meaning from product design, which comprises "the form characteristics of a product that provide utilitarian, hedonic, and semiotic benefits to the user" (Bloch, 2011, p. 378). Chitturi et al. (2008) show that design is relevant at the moment of adoption and then also influences consumers' post-adoption behavior. Perceptions of functional design aspects also prompt consumers' prevention orientations, which ultimately influence their satisfaction. Perceived hedonic design benefits instead evoke their promotion orientations and can lead to post-adoption delight. Therefore, the visual appearance of products has a strong influence on early adoption decisions, then influences the post-adoption product experience of the early adopters (Bloch, 1995, 2011; Chitturi et al., 2008). According to Bloch (1995), consumers respond to product forms in various ways, but overall, an appraisal of a product form leads to an aesthetic response, defined as a "deeply felt experience that is enjoyed purely for its own sake without regard for other more practical considerations" (Holbrook & Zirlin, 1985, p. 21). We refer to consumers' aesthetic response using the term "aesthetic product evaluation," to highlight the value derived solely from liking the product's appearance.

### **4.2.2. Buffering Halo Effect of Perceived Aesthetic Value**

Before their adoption, consumers can infer utility from product design but also from product descriptions and word of mouth. As soon as they have adopted the product, consumers start to gather experience, such that they learn by using the newly adopted product. Shih and Venkatesh (2004) show that greater experience affects the variety and rate of product usage. Consumers' utility also can be differentiated, as experienced hedonic or functional utility (Voss, Spangenberg, & Grohmann, 2003). Perceptions of

functional utility stem from rational evaluations of the product's usefulness; hedonic utility in the post-adoption phase instead relies on experienced product fun. Both types of utility contribute to attitudes toward the product (Voss et al., 2003), and consumers' appraisals of aesthetic value likely influence this attitude formation process too. Bloch (1995) argues that aesthetic value refers to both hedonic and functional aspects of a product: Aesthetic value entails sensory aspects of design and signals hedonic utility, comprised of "those facets of consumer behavior that relate to the multisensory, fantasy and emotive aspects of one's experience with a product" (Hirschman & Holbrook, 1982; p. 92). Aesthetic value also points to the functional purpose of a product, because visual appearance is a hint of functional performance. In the example Bloch (1995) offers, a race horse is perceived as most beautiful when it is running. Aesthetic value therefore signals functional utility, or benefits "derived from functions performed by products" (Voss et al., 2003; p.310).

According to Hoegg and Alba (2011), product form can create a halo effect on consumers' adoption decisions. When consumers like the product's visual appearance, they overestimate its usefulness, even if they gain information about its actual performance. Drawing on appearance bias research in social psychology (Hassin & Trope, 2000; Landy & Sigall, 1974; Langlois et al., 2000), they suggest that, just as personal attractiveness biases judgments of leadership skills or work quality, consumers' inferences based on product aesthetics have the potential to override considerations of objective product-related information. Along the same lines, we argue that visual aesthetics remain influential in the post-adoption phase, such that halo effects persist in the long term (Nisbett & Wilson, 1977). The same process that leads consumers to judge a product by its design rather than by its technical specifications is likely to affect their post-adoption product evaluations too. Consumers derive information about product usefulness and product fun from their aesthetic impressions (Creusen & Schoormans, 2005), so the main difference between the pre- and post-adoption phase is consumers' experience with the product. Before adoption, substantial uncertainty exists regarding true product performance, but in the post-adoption phase, consumers have first-hand experience with the product's fun and functionality. They are certain about the absolute level of hedonic and functional utility an innovation is able to provide. If visual impressions substitute for objective product-related information in the pre-adoption phase (Hoegg & Alba, 2011), the product's aesthetic value similarly might reduce the relevance of first-hand product-related experiences in the post-adoption phase. Therefore, an aesthetic response to an innovation could reduce the influence of actual product-



related experience on post-adoption attitudes. The halo effect, as identified in the adoption phase (Hoegg & Alba, 2011), thus might exist in the post-adoption phase too. The influence of consumers' actual experience with the product on their attitudes toward the product should become weaker when they derive more aesthetic value from the product throughout the post-adoption phase.

*H1: The better consumers' aesthetic product evaluation, the weaker the effect of their experienced (a) hedonic and (b) functional utility on attitudes toward the product in the post-adoption phase.*

### **4.2.3. Innate Consumer Innovativeness as a Moderator**

Consumers adopt innovations for multiple reasons. Sociodemographic variables offer strong explanatory power, such that early adopters tend to be well educated and have a high socio-economic status (Im, Bayus, & Mason, 2003; Rogers, 1995). However, they are not totally homogenous. Midgley and Dowling (1978) argue that proportionally many early adopters can be characterized by their higher levels of consumer innovativeness as a personality trait, which creates a desire to seek out the new and different (Hirschman, 1980). McDonald and Alpert (2007) therefore propose a stronger research focus on consumer innovativeness, due to its great potential for targeting early adopters. By moving beyond sociodemographics, innovation marketers could leverage what we know about psychologically innovative consumers and maximize the word of mouth that early adopters spread. The consumer innovativeness trait invokes some marketplace dynamics, by motivating consumers to demand innovation. In contrast, without any psychological desire to adopt novel products, "consumer behavior would consist of a series of routinized buying responses to a static set of products" (Hirschman, 1980, p. 283).

According to Steenkamp and Gielens (2003), consumer innovativeness is a generalized trait that positively affects the probability that consumers will try novel products and services. A close conceptual relationship thus exists between innate innovativeness and behavioral innovativeness. Behavioral innovativeness means the relatively earliness of consumers' adoption in the overall diffusion process (Midgley & Dowling, 1978; Rogers, 1995). The cohort of early adopters consists of people who are all behaviorally innovative, in the sense that they adopt a novel product long before the majority of the market. As Midgley and Dowling (1978) point out, the score on the generalized

consumer innovativeness trait increases a consumer's probability of being among the early adopters of a product. We therefore focus on consumer innovativeness as a generalized, innate, psychological trait, considering the close connection between the trait and the behavior (Midgley & Dowling, 1978; Steenkamp & Gielens, 2003). This trait perspective offers the richest stream of research on consumer innovativeness (Bartels & Reinders, 2011) and enables us to focus on general psychological effects, relevant to the adoption decisions of all cohorts of early adopters.

Truong et al. (2014) further report that purchase intentions are higher among innovative consumers when products have an innovative product form. The influence of perceived product aesthetics on purchase intentions therefore increases with consumers' levels of innovativeness. Attitudes toward a product at the time of the adoption decision, as well as in the post-adoption phase, depend on judgments of visual aesthetics (Chitturi et al., 2008). We therefore argue that consumer innovativeness increases the relevance of perceived aesthetic value in the post-adoption attitude formation process.

*H2: The effect of aesthetic product evaluations on attitudes toward the product in the post-adoption phase is stronger for customers with a high level of innate consumer innovativeness.*

#### **4.2.4. Moderating Influence of Consumer Innovativeness**

The relevance of aesthetics for innovative consumers likely affects the post-adoption halo effect we have predicted. Consumer innovativeness is focused on hedonic utility, and it is manifest in hedonic behaviors (Hirschman, 1980; Hirschman & Holbrook, 1982). More innovative consumers engage in more novelty and variety seeking, because of the hedonic utility they experience through these behaviors (Arnold & Reynolds, 2003; Childers, Carr, Peck, & Carson, 2002). Purchasing products is a means to satisfy their hedonic need for novelty and variety. Bloch (1995) argues that product aesthetics lead to both affective and cognitive responses. When making a purchase decision, innovative consumers value product appearance more than other customers, as manifested in their greater liking of product innovations (Truong et al., 2014). Noble and Kumar (2010) argue that affective responses result from holistic sensory properties rather than from utilitarian cues at the attribute level. The overall impression of a product leads to an affective reaction. Therefore, for innovative consumers, the holistic af-

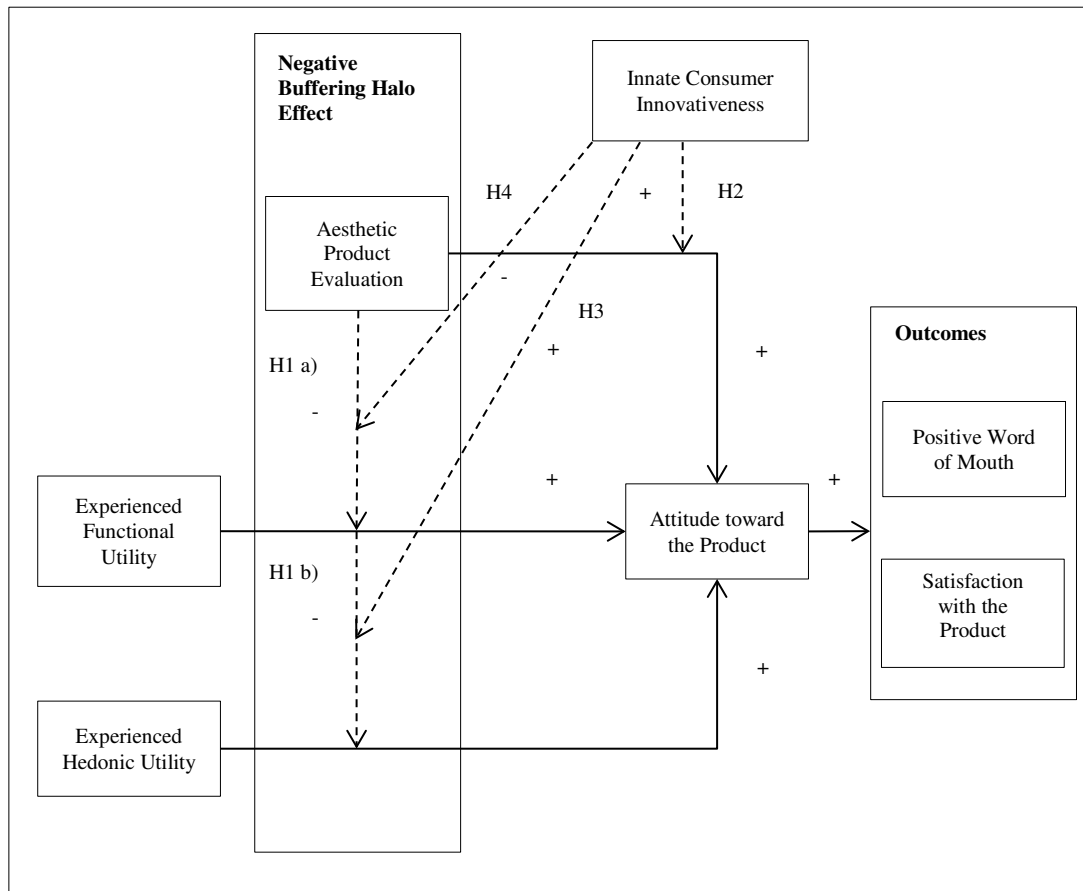
fective impression should carry over to the post-purchase phase. In line with these findings, we assume that consumer innovativeness strengthens the hedonic dimension of the halo effect. The hedonic aspect of a product's aesthetic also should lead to a stronger reduction of the influence of hedonic product experiences on attitudes toward the product among innovative consumers.

*H3: The buffering halo effect of aesthetic product evaluation on the influence of experienced hedonic utility on attitudes toward the product in the post-adoption phase is stronger for customers with a high level of innate consumer innovativeness.*

Bruner and Kumar (2007), investigating a domain-specific derivative of the general consumer innovativeness trait, argue that consumer innovativeness leads to a stronger focus on the product. Innovative consumers adopt for reasons related to the product, rather than due to social influences. At the start of the diffusion curve, virtually no word of mouth exists from peers. Similarly, Truong et al. (2014) report that perceptions of innovative product designs increase purchase intentions but also lead innovative consumers to value the product more. Product design results in cognitive and affective evaluations (Bloch, 1995). The cognitive responses include reasoning about the products' functional performance (Noble & Kumar, 2010), which then produces functional expectations (Hoegg & Alba, 2011). In the post-adoption phase, expectations encounter actual experience and provoke an evaluation process (Churchill & Surprenant, 1982). Due to their deeper reasoning about product performance and products' features, innovative consumers may be less affected by the halo effect pertaining to this functional experience. The buffering halo effect, reducing the influence of experienced functional utility on attitudes, thus should be weaker for innovative consumers.

*H4: The buffering halo effect of aesthetic product evaluations on the influence of experienced functional utility on attitudes toward the product in the post-adoption phase is weaker for customers with a high level of innate consumer innovativeness.*

**Figure 7**  
Conceptual Framework (Essay III)



## 4.3. Methodology

### 4.3.1. Sample

We chose the BMW i3 electric car as a focal innovation in this study. It is radically new in both its construction and design, such that its visual aesthetics differ from those of conventional cars (Figure 8).

**Figure 8**  
Aesthetic Impression of the BMW i3 (Essay III)



This product is thus ideal for investigating the research questions related to the post-adoption effects of aesthetic responses in the context of product innovations. We conducted a three-wave online survey among a sample of early BMW i3 adopters, namely, customers who purchased their vehicles before the middle of 2015, or within one and a half years of its market launch. At that time, the market for electric vehicles in Germany was just beginning; there were no subsidies or tax benefits for buyers of electric cars. In a small pre-survey, we asked participants about their demographics and measured the innate consumer innovativeness psychological trait. We then contacted these customers two weeks later, with the first wave of the longitudinal survey. Next, we contacted the customers again three months later, after they had gained more usage experience. The time gaps were equivalent for all participants. Finally, we reached out to the same respondents six months later. Consumers who responded to all three survey waves entered the final sample. We imputed missing values on any single items that were part of multi-item scales using the scale mean of the specific respondent. This

procedure applied to 0.67% of all measured values. For this longitudinal study, this procedure prevented 64 cases from being excluded from the analysis. The sample of early adopters ultimately consisted of 179 respondents.

### 4.3.2. Study Design

The study design aims to investigate the role of perceived aesthetic value and innate consumer innovativeness in the post-adoption context. The longitudinal structure resulting from gathering repeated measures from the same consumers over time enables us to control for time-invariant unobserved heterogeneity (Wooldridge, 2010). The models include fixed effects for the respondents and exclusively use within-subject variance, resulting from changes in individual responses from measurement wave to measurement wave. The interaction terms between the time-invariant variable that measures innate consumer innovativeness and the changing aesthetic product evaluations reveal causal links regarding the role of this personality trait in the particular context. Causality exists for two reasons. First, consumer innovativeness is a personality trait, reflecting a routinized shopping behavior (Bartels & Reinders, 2011; Hirschman, 1980; Midgley & Dowling, 1978; Steenkamp & Gielens, 2003), so it can be regarded as stable for the time span of our analysis. Second, the fixed effects control for the time-constant error term of the regression equations. The results therefore offer causal reliability, which comes close to an experimental design.

### 4.3.3. Measures

The study measures are in Table 24. The constructs were measured using 6- and 7-point, multi-item, Likert-type agreement scales, as well as a semantic differential scale. The items in each scale appeared in a completely randomized order to minimize the risk of a measurement bias. We measured innate consumer innovativeness using four items from Steenkamp and Gielens (2003); it is a time-invariant construct. To avoid biasing the measure of consumer innovativeness with consumers' implicit theories about the investigation, we included this measure in the pre-survey. The scale reliability was good ( $\alpha = 0.80$ ). The constructs in the longitudinal study were measured repeatedly across all three study waves. Specifically, *attitude toward the product* was measured by five items from the attitude toward the high-tech product measure from Tybout et al. (2005). The reliability of the measure remained consistently good ( $\alpha_{t1} = 0.80$ ,  $\alpha_{t2} = 0.79$ ,  $\alpha_{t3} = .84$ ). We operationalized *aesthetic product evaluation* with four items from the aesthetic

response to the product measure of Lam and Mukherjee (2005) and three innovation-specific items, to reflect our product innovation context. This measurement also was reliable across all survey waves ( $\alpha_{t1} = 0.81$ ,  $\alpha_{t2} = 0.83$ ,  $\alpha_{t3} = 0.83$ ). Consumers' *satisfaction with the product* was measured by five general items (Brown, Barry, Dacin, & Gunst, 2005) and five items that captured important satisfaction aspects specific to electric cars ( $\alpha_{t1} = 0.73$ ,  $\alpha_{t2} = 0.76$ ,  $\alpha_{t3} = 0.79$ ). We measured *experienced hedonic utility* using a five-item scale from Uhrich, Schumann, and von Wangenheim (2013), and *experienced functional utility* featured three items from the same authors. Both scales were adapted versions of Voss et al.'s (2003) scales. Again, the reliability was high for all measurement waves, for both experienced hedonic utility ( $\alpha_{t1} = 0.83$ ,  $\alpha_{t2} = 0.81$ ,  $\alpha_{t3} = 0.85$ ) and experienced functional utility ( $\alpha_{t1} = 0.70$ ,  $\alpha_{t2} = 0.77$ ,  $\alpha_{t3} = 0.75$ ). We measured *positive word of mouth* using two items from Arnett, German, and Hunt (2003) that assessed actual word-of-mouth behavior. The correlation of these two items was strong for all measurement waves ( $r_{t1}(179) = .59$ ,  $p < .001$ ;  $r_{t2}(179) = .55$ ,  $p < .001$ ;  $r_{t3}(179) = .77$ ,  $p < .001$ ).

**Table 24**  
Measures, Scale Items, Type, and Origin (Essay III)

Measure	Scale Items	Type	Origin
Innate Consumer Innovativeness	<ol style="list-style-type: none"> <li>1. In general, I am among the first to buy new products when they appear on the market.</li> <li>2. I am usually among the first to try new products or brands.</li> <li>3. I enjoy taking chances in buying new products.</li> <li>4. When I discover a new product on the shelf, I am tempted to give it a try.</li> </ol>	6-point Likert scale, strongly disagree to strongly agree	Adapted from Steenkamp & Gielens (2003)
Attitude Toward the Product	<ol style="list-style-type: none"> <li>1. I like the BMW i3.</li> <li>2. The BMW i3 is impressive.</li> <li>3. The BMW i3 is desirable.</li> <li>4. The BMW i3 is advanced.</li> <li>5. The BMW i3 is cutting-edge technology.</li> </ol>	6-point Likert scale, strongly disagree to strongly agree	Adapted from Tybout et al. (2005)
Aesthetic Product Evaluation	<ol style="list-style-type: none"> <li>1. Poor-looking/nice-looking</li> <li>2. Displeasing/pleasing</li> <li>3. Unattractive/attractive</li> <li>4. Beautiful/ugly*</li> <li>5. Conventional/innovative</li> <li>6. Usual/futuristic</li> <li>7. Tame/arousing</li> </ol>	7-point semantic differential	Adapted from Lam & Mukherjee (2005)
Experienced Hedonic Utility	Using the BMW i3 is... <ol style="list-style-type: none"> <li>1. Fun</li> <li>2. Exciting</li> <li>3. Delightful</li> <li>4. Thrilling</li> <li>5. Enjoyable</li> </ol>	6 point Likert scale, strongly disagree to strongly agree	Adapted from Uhrich et al. (2013)

(continued)



(continued)

Experienced Functional Utility	Using the BMW i3 is... 1. Effective 2. Helpful 3. Practical	6 point Likert scale, strongly disagree to strongly agree	Adapted from Uhrich et al. (2013)
Satisfaction with the Prod- uct	How satisfied are you with the fol- lowing aspects of the BMW i3? 1. Appearance 2. Safety 3. Price 4. Quality 5. Power 6. Features 7. Driving Fun 8. Charging Frequency 9. Driving Range 10. Road Capability	7 point Likert scale, strongly disagree to strongly agree	Adapted from Brown et al. (2005)
Positive Word of Mouth	1. I the last three months, I "talked up" the BMW i3 to people I know. 2. In the last three months, I often spoke favorably about the BMW i3.	6-point Likert scale, strongly disagree to strongly agree	Adapted from Arnett et al. (2003)

Notes: \* Reverse coded item.

## 4.4. Results

### 4.4.1. Descriptive Statistics

The descriptive statistics in Table 25 inform the subsequent correlation analysis, using the pooled data that consist of complete information from the three survey waves. The average participant is 52 years of age ( $M = 51.93$ ,  $SD = 9.49$ ), with 163 male and 16 female respondents in the sample. Furthermore, 59% of respondents have a graduate degree. These characteristics are in line with the properties of early adopters we know from diffusion of innovation theory (Rogers, 1995), and they also fit well with the results of other studies in Germany focusing on early adopters of electric vehicles (Wietschel et al., 2014). The variables measuring consumers' aesthetic product evaluations ( $M = 5.73$ ,  $SD = 0.77$ ), experienced hedonic ( $M = 5.32$ ,  $SD = 0.66$ ) and functional utility ( $M = 5.17$ ,  $SD = 0.65$ ), attitudes toward the product ( $M = 5.37$ ,  $SD = 0.55$ ), satisfaction with the product ( $M = 5.85$ ,  $SD = 0.52$ ), and positive word-of-mouth behavior ( $M = 5.51$ ,  $SD = 0.68$ ) together indicate that early adopters tend to be very satisfied with the product and its visual aesthetics. Consumer innovativeness, measured on a 6-point Likert scale, has a mean value of 3.53 ( $M = 3.53$ ,  $SD = 1.06$ ). Although this study features a sample of early adopters, who should exhibit a greater likelihood of being innovative (Midgley & Dowling, 1978), we still find substantial natural variance in consumers' innate innovativeness. In fixed effects regression models effect heterogeneity can be modelled on a group level by allowing for an interaction between the treatment and the group. Although the time-invariant group effects are not identified, the results reveal if the treatment effect differs between groups. We hence group innate consumer innovativeness into high ( $> 3.50$ ) and low values ( $\leq 3.50$ ) at the median of the continuous measure.

**Table 25**  
Summary Statistics (Essay III)

Variables	Min	Max	Median	Mean	SD
INNO	1.25	6.00	3.50	3.53	1.06
ATTITUDE	3.40	6.00	5.40	5.37	0.55
DESIGN	3.14	7.00	5.86	5.73	0.77
HEDONIC	3.00	6.00	5.60	5.32	0.66
FUNCTION	3.33	6.00	5.00	5.17	0.65
PSATIS	3.20	6.80	5.90	5.85	0.52
POSWOM	3.00	6.00	6.00	5.51	0.68
AGE	24.00	80.00	51.00	51.93	9.49
GENDER	0.00	1.00	-	0.09	-
INCOME	0.00	1.00	-	0.30	-
EDUC	0.00	1.00	-	0.59	-

Notes:  $N \times T = 537$  ( $T = 3$  waves with  $N = 179$  respondents), AGE = age; GENDER = gender dummy, where 1 indicates female and 0 male respondents; EDUCATION = education dummy, where 1 is a graduate degree and 0 is no graduate degree; INCOME = income dummy, where 1 is household net income above 7500 Euros per month and 0 is below 7500 euros per month; INNO = innate innovativeness; DESIGN = aesthetic product evaluation; HEDONIC = experienced hedonic utility; FUNCTION = experienced functional utility; ATTITUDE = attitude toward the innovation; PSATIS = satisfaction with the product; POSWOM = positive word of mouth.

Our regression models feature individual fixed effects, such that our estimates stem from the within-subject variance in all three survey waves, as detailed in Table 26. The temporal distance between survey waves was three months, so the measures systematically vary on a small scale. Attitude toward the product varies between  $-0.93$  and  $0.80$  within individuals ( $Min = -0.93$ ,  $Max = 0.80$ ,  $SD = 0.28$ ). Positive word of mouth exhibits the greatest variation from the individual means ( $Min = -2.33$ ,  $Max = 2.67$ ,  $SD = 0.38$ ).

**Table 26**  
Summary Statistics (Within Variance) (Essay III)

Variables	Min	Max	SD
ATTITUDE	-0.93	0.80	0.28
DESIGN	-1.29	1.14	0.30
HEDONIC	-1.27	1.27	0.32
FUNCTION	-1.33	1.22	0.37
PSATIS	-1.60	1.10	0.25
POSWOM	-2.33	2.67	0.38

Notes:  $N \times T = 537$  ( $T = 3$  waves with  $N = 179$  respondents).

#### 4.4.2. Early Versus Late Respondents

We conducted an analysis of early versus late respondents to check for a potential bias due to the attrition rate, which is a common problem in longitudinal studies (Winer, 1983). That is, respondents might drop out from one measurement wave to the next for non-random reasons, which would lead to self-selection biases in the longitudinal study. As we show in Table 27, we obtained 247 valid online interviews in the first wave. The final sample consists of 179 customers who participated in all three survey waves, so the overall attrition rate is 27%, leaving 68 non-responders. To test for potential self-selection bias, we compared the respondents to non-respondents statistically, on the basis of the first survey. The results in Table 27 indicate that the samples do not differ in terms of their gender, education, or income composition. We also compared the means using Welch's t-test and find significant mean differences only in age and attitude toward the product: Respondents were a little bit younger ( $M_{\text{Non-Respondents}} = 54.64$ ,  $M_{\text{Respondents}} = 51.93$ ) and had slightly more positive attitudes ( $M_{\text{Non-Respondents}} = 5.17$ ,  $M_{\text{Respondents}} = 5.37$ ) in the first survey wave. Critically though, we find no self-selection bias in relation to innate consumer innovativeness, and the samples are largely comparable, so our final sample does not appear affected by a serious self-selection bias.

**Table 27**  
Early versus Late Responders Analysis (Essay III)

Variables	Non-Responders		Responders		T-Test		
	M	SD	M	SD	t-value	Df	p-value
AGE	54.64	9.57	51.93	9.49	1.99	120.1	0.05
GENDER	0.11	-	0.09	-	-	-	-
EDUCATION	0.65	-	0.59	-	-	-	-
INCOME	0.31	-	0.30	-	-	-	-
INNO	3.62	1.27	3.53	1.06	0.53	104.49	0.59
ATTITUDE	5.17	0.67	5.37	0.55	-2.09	102.83	0.04
DESIGN	5.75	0.78	5.73	0.77	0.18	118.98	0.85
HEDONIC	5.27	0.75	5.32	0.66	-0.54	108.67	0.58
FUNCTION	5.28	0.64	5.17	0.65	1.22	123.56	0.22
POSWOM	5.57	0.74	5.51	0.68	0.65	112.35	0.51
PSATIS	5.70	0.71	5.85	0.52	-1.66	96.01	0.09

Notes: N = 247 (Responders N = 179, Non-Responders N =68).

Table 28 contains the results of our correlation analyses for the pooled data set. The variables are significantly correlated, at moderate strength. Interactions between the time-invariant trait innate consumer innovativeness and the time-varying product evaluations are part of our subsequent hypotheses tests. Innate consumer innovativeness is significantly and negatively correlated with experienced functional utility. We find no further correlation between innate consumer innovativeness and other variables though. Consumer innovativeness is uncorrelated with attitude toward the product, which is the dependent variable we use subsequently in the multiple linear regression models (Tables 29 - 31). This insignificant direct relationship with attitude toward the product leads us to understand innate consumer innovativeness as a pure moderator variable (Sharma, Durand, & Gur-Arie, 1981). The correlation between attitude toward the product and experienced hedonic utility is stronger than the correlation with experienced functional utility. The electric car thus is a hedonic product innovation.

**Table 28**  
Correlation Matrix (Essay III)

Variables	1.	2.	3.	4.	5.	6.
1. INNO	-					
2. DESIGN	-.03	-				
3. HEDONIC	.02	.38***	-			
4. FUNCTION	-.15***	.24***	.39***	-		
5. ATTITUDE	.01	.47***	.70***	.44***	-	
6. PSATIS	-.05	.45***	.52***	.43***	.52***	-
7. POSWOM	-.03	.24***	.41***	.38***	.48***	.47***

Notes:  $N \times T = 537$  ( $T = 3$  waves with  $N = 197$  respondents) \*\*\*  $p < .001$ , \*\*  $p < .01$ , \*  $p < .05$ .

#### 4.4.3. Hypotheses Tests

We use information from all three survey waves, available from 179 customers ( $N \times T = 537$ ), to test H1–H4. We included fixed effects for the individual respondents when we specified models M1–M14.<sup>2</sup> As common in regression models containing fixed effects, there were no direct effects of time-invariant variables identified in the regression; using fixed effects means that the model perfectly controls for all time-invariant observed and unobserved influences, and thus for innate consumer innovativeness in the models. The regression results in Table 29 are organized into categories: basic models (M1 and 2), hedonic halo models (M3–5), and functional halo models (M6–M8).

<sup>2</sup> The fixed effects transformation controls for the time-invariant error term:  $(y_{ti} - \bar{y}_i) = \beta(x_{ti} - \bar{x}_i) + (\varepsilon_{ti} - \bar{\varepsilon}_i)$ .

Table 29  
Multiple Linear Regression Predicting: Attitude Toward the Product (Essay III)

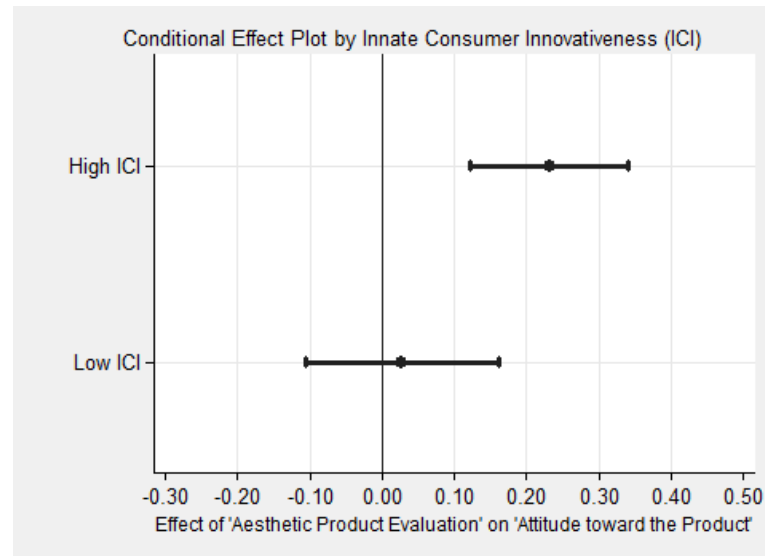
	Basic Models			Hedonic Halo Models		Functional Halo Models		
	M1	M2	M3	M4	M5	M6	M7	M8
DESIGN	0.13** (0.04)	0.03 (0.06)	0.61** (0.23)	0.50** (0.24)	0.02 (0.33)	0.55* (0.22)	0.36 (0.24)	0.69 (0.37)
HEDONIC	0.20*** (0.04)	0.20*** (0.04)	0.70** (0.24)	0.71** (0.24)	0.20 (0.34)	0.20*** (0.04)	0.20*** (0.04)	0.19*** (0.04)
FUNCTION	0.17*** (0.04)	0.17*** (0.04)	0.17*** (0.04)	0.17*** (0.04)	0.17*** (0.04)	0.62** (0.24)	0.56* (0.25)	0.89* (0.37)
DESIGN × HEDONIC			-0.09* (0.04)	-0.09* (0.04)	0.00 (0.06)			
INNO × DESIGN		0.20* (0.09)		0.20* (0.09)	1.14* (0.46)		0.19* (0.09)	-0.35 (0.47)
INNO × HEDONIC				-0.03 (0.08)	0.95* (0.47)			
INNO × DESIGN × HEDONIC					-0.18* (0.08)			
DESIGN × FUNCTION						-0.08 (0.04)	-0.06 (0.04)	-0.12 (0.07)
INNO × FUNCTION							-0.08 (0.07)	-0.65 (0.49)
INNO × DESIGN × FUNCTION								0.10 (0.09)
Observations	537	537	537	537	537	537	537	537
R <sup>2</sup>	0.17	0.19	0.18	0.20	0.21	0.18	0.19	0.20

Notes: N × T = 537 (T = 3 waves with N = 179 respondents). This fixed effects models uses within-subject variance across the three survey waves. Time-invariant person-related variables are thus perfectly controlled, which also applies to the unidentified direct effect of consumer innate innovativeness. Standard errors are in brackets. \*\*\*  $p < .001$ , \*\*  $p < .01$ , \*  $p < .05$ .

The F-tests of all models are significant. To prepare for the subsequent hypotheses tests, all of which involve interaction effects, we first estimated basic models that showed the influence of product-related hedonic and functional usage experience, perceived aesthetic value (M1), and its interaction with consumer innovativeness (M2) on attitudes toward the product. Model M1 shows that the independent variables all are significantly and positively related to attitude toward the product. The variables explain 17% ( $R^2 = .17$ ) of the within-subject variance in attitudes toward the product ( $F(3,355) = 24.79, p < .001$ ). The influence of changes in experienced hedonic utility ( $b = .20, p < .001$ ), functional utility ( $b = .17, p < .001$ ), and aesthetic product evaluation ( $b = .13, p < .01$ ) on changes in attitudes toward the product is significant. In model M2, we investigate the potential positively moderating effect of innate innovativeness on the relationship between changes in consumers' aesthetic product evaluation and attitude, as postulated in H2. The model is significant overall ( $F(4,354) = 20.21, p < .001$ ) and accounts for 19% of the within-subjects variance ( $R^2 = .19$ ) in attitudes toward the product. The interaction term between innate consumer innovativeness and changes in aesthetic product evaluation emerges as positive and significant ( $b = .20, p < .05$ ); Figure 9 illustrates the interaction between consumers' levels of innate innovativeness and changes in aesthetic product evaluations. We thus confirm H2.



**Figure 9**  
Conditional Effects Plot (Essay III)



Model M3 extends M1, and we estimated it to test H1, namely, the prediction of a halo effect of consumers' aesthetic product evaluation that buffers the influence of product-related hedonic experience on consumers' attitudes toward the product over time. M3 explains 18% of within-subject variance ( $R^2 = .18$ ) and is highly significant ( $F(4,354) = 19.90, p < .001$ ). The interaction term between changes in experienced hedonic utility and aesthetic product evaluation negatively influences the effect of changes in experienced hedonic utility on attitudes toward the product ( $b = -.09, p < .05$ ), in support of H1a.

We continue to investigate the three-way interaction of innate innovativeness with the basic halo effect shown in model M3. For this three-way analysis to achieve a meaningful interpretation, we must find a significant influence of an interaction term when all three interaction terms are specified in the model. As M4 ( $F(6,352) = 14.31, p < .001$ ) shows, controlling for all three possible interactions, the moderating influence of innate innovativeness on the relationship between consumers' aesthetic product evaluations and attitudes toward the product ( $b = .20, p < .05$ ), as well as the halo effect on experienced hedonic utility ( $b = -.09, p < .05$ ), are significant. Accordingly, M4 explains 20% of the within-subject variance in attitudes toward the product ( $R^2 = .20$ ). The test of H3 relies on the three-way interaction term among innate consumer innovativeness, individual changes in aesthetic product evaluations, and experienced hedonic utility. Model M5 ( $F(7,351) = 13.00, p < .001$ ) shows that the buffering halo effect from M3

additionally interacts with consumers' levels of innate innovativeness ( $b = -.18, p < .05$ ). To interpret the significant three-way interaction present in M5, we break the sample down into a sample of highly innovative customers and a sample of customers with below or equal the median values in innate consumer innovativeness. We specify models M9-12, shown in table 30, to interpret the hedonic halo effect in both sub-samples.

**Table 30**  
Multiple Linear Regressions Predicting: Attitude Toward the Product  
(Median Split) (Essay III)

	Low INNO		High INNO	
	M9	M10	M11	M12
DESIGN	0.03 (0.06)	0.01 (0.34)	0.24*** (0.06)	1.17*** (0.30)
HEDONIC	0.20*** (0.06)	0.18 (0.36)	0.20*** (0.06)	1.16*** (0.31)
FUNCTION	0.21*** (0.06)	0.21*** (0.06)	0.13** (0.05)	0.13** (0.05)
DESIGN × HEDONIC		0.00 (0.06)		-0.18** (0.06)
<i>Observations</i>	285	285	252	252
<i>R</i> <sup>2</sup>	0.15	0.15	0.23	0.27

*Notes:* Regressions on the two samples obtained from the median split on INNO.  $N_{Low\ Inno}$  = 285 (T = 3 waves with N = 95 respondents),  $N_{High\ Inno}$  = 252 (T = 3 waves with N = 84 respondents). The models include individual fixed effects. \*\*\*  $p < .001$ , \*\*  $p < .01$ , \*  $p < .05$ .

Model 12 shows that the interaction between changes in aesthetic product evaluation and hedonic utility is only significant in the part of the sample consisting of consumers with above median scores in innate consumer innovativeness ( $b = -.18$ ,  $p < .01$ ). The hedonic halo effect does not exist for customers low in innate innovativeness, but exists for customers with above median scores in innate consumer innovativeness. We accept H3.

Next, we discuss the results of models M6–M8, which provide the tests of H1b and H4, related to the relationship between attitudes toward the product and experienced functional utility over time. For H1b, regarding the buffering halo effect of consumers' aesthetic product evaluations on the relationship between experienced functional utility and attitudes, we estimated M6 ( $F(4,354) = 19.64$ ,  $p < .001$ ) and found that 18% of the within-subject variance in attitudes toward the product could be explained by the independent variables ( $R^2 = .18$ ). The interaction term between individual changes in perceived aesthetic value and experienced functional utility was negative and significant (10% alpha level,  $b = -.08$ ,  $p = .05$ ). We therefore confirm H1b. We also postulated that

innate consumer innovativeness weakens the halo effect of consumers' aesthetic product evaluations on attitudes toward the product over time. Similar to model M4, we specified M7 as a prerequisite of the three-way interaction analysis ( $F(6,352) = 14.07$ ,  $p < .001$ ). This model accounts for 19% ( $R^2 = .19$ ) of the within-subject variance. The negative halo effect of perceived aesthetic value on the influence of experienced functional utility is not significant ( $b = -.06$ ,  $p > .10$ ). Furthermore, the interaction effect between innate consumer innovativeness and individual changes in consumers' aesthetic product evaluation, initially investigated in M2, remains significant when the model controls for all three possible interactions relevant to the three-way interaction ( $b = .19$ ,  $p < .05$ ). We therefore proceeded and specified model M8 ( $F(7,351) = 12.27$ ,  $p < .001$ ), which accounts for 20% of the within-subject variance in attitudes toward the product ( $R^2 = .20$ ) and includes a three-way interaction term among innate consumer innovativeness, changes in consumers' aesthetic product evaluation, and experienced functional utility. Although the interaction term has the expected positive sign, the term is insignificant ( $b = .10$ ,  $p > .10$ ), so we must reject H4.

To illustrate the relevance of attitude toward the product, we estimated its intertemporal influence on positive word of mouth in M13 and customer satisfaction in M14. Both models include fixed effects for every respondent, such that we only specify the direct effect of attitudes on the respective outcome variable. All the time-invariant influences related to the individual respondent are perfectly controlled for, through the fixed effects. As the results in Table 31 show, M13 ( $F(1,357) = 24.94$ ,  $p < .001$ ) explains 7% ( $R^2 = .07$ ) of the variance in consumers' positive word-of-mouth behavior. Attitude toward the product significantly and positively influences the amount of word of mouth spread by customers ( $b = .36$ ,  $p < .001$ ). Model M14 ( $F(1,357) = 12.57$ ,  $p < .001$ ) accounts for 3% ( $R^2 = .03$ ) of the within-subject variance in product satisfaction; this low explanatory power might reflect the conceptual distance between attitude and satisfaction. That is, attitude reflects product liking, whereas satisfaction represents a rational evaluation of the product's strengths and weaknesses (Churchill & Surprenant, 1982). When all other time-invariant variables are perfectly controlled, the relationship turns out to be weak. Changes in attitudes toward the product nevertheless have significant positive influences on individual changes in the customers' satisfaction with the product ( $b = .17$ ,  $p < .001$ ).

**Table 31**  
Multiple Linear Regressions Predicting: Positive Word of Mouth and  
Product Satisfaction (Essay III)

	Dependent Variables	
	POSWOM	PSATIS
	M13	M14
ATTITUDE	0.36*** (0.07)	0.17*** (0.05)
<i>Observations</i>	537	537
<i>R<sup>2</sup></i>	0.07	0.03

*Notes:* \*\*\* p < .001, \*\* p < .01, \* p < .05

## 4.5. Discussion

This study deals with the effect of consumers' aesthetic product evaluations in post-adoption phases. Using longitudinal data from early adopters of the BMW i3 electric car in Germany, we have shown that the perceived aesthetic value causes a buffering, halo effect in the post-adoption phase. The more positively consumers evaluate the products' visual aesthetics, the weaker the dependence of their attitude on actual product-related hedonic and functional experiences (H1a, H1b). The innate personality trait of consumer innovativeness also systematically influences the impact of this perceived aesthetic value on attitudes over time. When consumers seek out and purchase novel products, the influence of an aesthetic product evaluation is stronger on their attitudes, throughout the post-adoption phase (H2). As a consequence, innate consumer innovativeness moderates the halo effect of aesthetic product evaluations on the relationship between experienced hedonic utility and attitude (H3). Innate consumer innovativeness influences the halo effect such that a hedonic halo effect only exists for consumers with higher scores in this personality trait. However, we could not confirm our prediction that innate consumer innovativeness would weaken the halo effect for experienced functional utility (H4).

### 4.5.1. Theoretical Implications

This study offers three key contributions to theory about the role of consumer innovativeness (Bartels & Reinders, 2011) and product form for product innovation adoption decisions (Hoegg & Alba, 2011; Truong et al., 2014). First, we show that the aesthetic value of products remains strongly relevant to innovative consumers, beyond the moment of adoption. The more consumers purchase novel products, the greater is the influence of their aesthetic product evaluation on their attitudes toward the product over time. The aesthetic thus exerts a strong influence on purchase intentions (Truong et al., 2014) and also has a more general effect on innovative customers' experience, including their post-purchase product appraisal. Innate consumer innovativeness is a prevalent trait among early adopters (McDonald & Alpert, 2007; Midgley & Dowling, 1978), and many prior studies regard innovative consumers as opinion leaders (Girardi, Soutar, & Ward, 2005; Goldsmith, Flynn, & Goldsmith, 2003; Goldsmith, Kim, Flynn, & Kim, 2005). Later adopters rely on the early adopters' experiences when considering their own purchases. Our finding that consumers' aesthetic product evaluation is a stronger driver of the attitudes of more innovative consumers therefore is highly relevant to the diffusion of innovation theory (Rogers, 1995).

Second, we extend research into the role of product design in the innovation adoption process (Chitturi et al., 2008; Creusen & Schoormans, 2005; Hoegg & Alba, 2011) by identifying the halo effect that persists into the post-adoption phase. In the post-adoption attitude formation process, consumers assign less weight to their own objective usage experience when they like the products' visual aesthetics better. Before adoption, consumers' evaluations of the product form create a halo effect that induces them to infer product functionality from the innovative product form, even if those consumers also have access to objective information about the product's true performance (Hoegg & Alba, 2011). In the post-adoption phase, the halo effect thus not only applies to experienced product functionality but also reduces the influence of the consumers' experience of product fun in the attitude formation process. In the post-adoption phase, product fun turns from a subjective expectation into objective information, such that consumers gather first-hand information about fun and product functionality. This first-hand experience represents objective information, overlaid by visual impressions in the attitude formation process over time.

Third, we extend existing research on both the halo effect (Hoegg & Alba, 2011) and the interplay of consumer innovativeness and aesthetics (Truong et al., 2014). Combining these research streams, we determine that the halo effect of product form (Hoegg & Alba, 2011) only exists for hedonic experiences when consumers are more strongly characterized by their innate consumer innovativeness personality trait. Innate innovativeness relates closely to hedonic types of behavior (Hirschman, 1980; Hirschman & Holbrook, 1982), and hedonic motives often guide the shopping behaviors of innovative consumers (Childers et al., 2002). Accordingly, we find that the post-adoption halo effect buffers the influence of experienced product fun on attitudes only when consumers are more innovative. We anticipated that innate consumer innovativeness would increase consumers' awareness of experienced functional utility, because innovative consumers reason more about functionalities, such that we expected a weaker buffering halo effect of functional experience. Although the results of our correlation analysis indicate that innate innovativeness leads to poorer evaluations of experienced functional utility in the post-adoption phase, and though the three-way interaction term among functional experience, innate innovativeness, and product form showed the expected positive sign, we could not find sufficient empirical support for the hypothesis that the halo effect would be weaker for innovative consumers when it buffers functional utility. We posit that aesthetic evaluations might occur on the holistic product level (Noble & Kumar, 2010), rather than on the level of individual features. Therefore, the halo effect of product form would operate on the global level too, and even influence innovative consumers' functional experience. To find a significant negative effect, we would likely need to investigate halo effects at the concrete level of functional experience, using specific, isolated features and the perceived value of single design elements.

#### **4.5.2. Managerial Implications**

This study also offers three important managerial implications. First, we show that consumers' aesthetic product evaluation creates a long-term halo effect, dissociating product attitude from actual product-related experiences. Therefore, managers need to recognize that visual aesthetics are more than a means to convince consumers to adopt. Marketing practice in an innovation setting usually entails providing consumers with rational arguments about product advantages and usefulness. We show that products' aesthetic value continues to exert important influences in the post-adoption phase too. Changes in perceived aesthetic value over time buffer individual changes in experienced utility and attitude. Product aesthetics are a manageable factor, relevant to both

adoption and the post-purchase product experience. We therefore recommend that managers actively co-create product forms with potential customers to generate aesthetics that those consumers will appreciate or even fall in love with over time (Hoyer, Chandy, Dorotic, Krafft, & Singh, 2010), such as when a product's aesthetics set a new design trend.

Second, when selecting partners for co-creation efforts dedicated to developing product aesthetics, we recommend finding consumers who frequently purchase novel products, because their higher levels of innovativeness should increase their chances of being among the early adopters of any innovation (Midgley & Dowling, 1978). To test this conceptual proposition, we conducted another survey with a sample representative of potential car buyers in Germany ( $N = 1000$ ). With a t-test, we compared the mean innate consumer innovativeness of the potential early majority ( $N = 270$ ) with that of the entire consumer population. The early majority exhibited significantly higher levels of innate consumer innovativeness on average ( $M = 3.44$ ,  $SD = 1.29$ ) than the overall population ( $M = 2.97$ ,  $SD = 1.26$ ;  $t(1268) = -5.25$ ). This finding supports the theoretical reasoning offered by Midgley and Dowling (1978): Members of cohorts early in the diffusion process have higher average values of innate consumer innovativeness than do later adopters. If they seek to match the aesthetic tastes of potential early adopters, managers should interview consumers with high innate innovativeness scores and invite them to co-creation workshops. To screen the population, they might use standardized psychometric scales that can measure consumer innovativeness (Steenkamp & Gielens, 2003).

Third, design co-creation with innovative consumers may offer another advantage. Innovative consumers are powerfully affected by the halo effect, dissociating product-related hedonic experience from attitude in the post-adoption phase. Managers thus can strengthen the halo effect on product fun for these customers. Considering the greater level of innate innovativeness among early adopters, the level of hedonic utility provided by product innovations thus may be less decisive than generally assumed.



### 4.5.3. Limitations and Further Research

This study has some limitations that suggest avenues for further research. For example, we investigated only one product and its aesthetic value, which offered the advantage of being able to study the within-subject variance in a longitudinal survey to reveal the existence of a halo effect, with perfect control of time-invariant heterogeneity. However, it restricted our study to a single product design. Our general focus on aesthetic value suggests a question about whether certain aspects within the product form concept might be optimized to strengthen the halo effect. Further research should systematically compare products with different product forms in the pre- and post-adoption phases to strengthen theoretical understanding of the halo effect. In the pre-adoption phase, researchers could investigate the relative impact of aesthetic facets, such as product newness, product simplicity, or complexity, on the halo effect, compared with the influence of objective, product-related information (Hoegg & Alba, 2011). In the post-adoption phase, field experiments with novel products exhibiting different product forms could be conducted to investigate the influence of product newness, simplicity, and complexity on the negative halo effect as it relates to customers' first-hand usage experience with products.

We also focused on the interplay of innate consumer innovativeness with perceived aesthetic value. Further research might look more specifically at the interplay of consumer innovativeness and halo effects before adoption. As Truong et al. (2014) show, perceived product newness is an aesthetic quality that resonates with consumer innovativeness before product adoption. Researchers should investigate if consumer innovativeness also has a moderating effect on the halo effect Hoegg and Alba (2011) identify in a purchase context.



## 4.6. References

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## 5. Conclusion

This dissertation consists of three empirical essays covering different aspects of innovation marketing. In the first essay, I deal with the core members' motivation to collaborate with members located in the periphery of innovation forums. The second essay identifies a product launch strategy for radical disruptive innovations. In the third essay, we provide evidence for a post-adoption halo effect of aesthetic value in early adopters' attitude formation process. Hence, all three essays offer individual implications to contemporary research in innovation marketing. The following discussion summarizes the theoretical implications to highlight the overall contribution of this dissertation. After that, I discuss limitations of my dissertation and provide suggestions for further research.

### 5.1. General Discussion

The first essay contributes to our understanding of innovative performance in online communities. Its aim was to identify a reason why core members collaborate with members from the periphery in innovative online forums. The essay explores the exchange process between core members and the periphery. The study shows that core members can increase their expert influence among peers in the core over time by actively exchanging with the periphery. Furthermore, the essay explains this effect by revealing the underlying process. The first essay makes several contributions. First, core members can increase their expert influence amongst their peers over time, given an increase of their involvement with the periphery. This extends existing research in that it provides us with the counterpart to the explanation how peripheral members profit from exchanging with the community core. Dahlander and Frederiksen (2012) found that by gradually coming closer to the core, peripherals can increase their innovative performance. Second, by revealing the benefits which an active exchange with the periphery provides for core members, the essay provides the micro foundations to what has been observed to happen on the macro level. Research frequently has argued that the entire community profits from the exchange processes between core and periphery (Dahlander & Frederiksen, 2012; Rullani & Haefliger, 2013). In the logic of methodological individualism (Coleman, 1986), the relationship between core and periphery is a social macro level explanation which still needed a theoretical micro level explanation. Third, the essay shows the process by which contacts to the periphery help members to

improve their expert influence in the core. The periphery is the social sphere where ideas are more radical. Involving into discussions in the periphery hence creatively stimulates the members such that they can contribute more mindfully to peers in the core. It enables the core member to reach out to a greater number of peers which results in an increase in expert influence.

Managers should focus on core members in vital exchange with the periphery when sending out invitations to co-creation workshops. The finding that peripheral contacts increase the members' expert influence in the core can be used by practitioners as an additional criterion which experts to invite. Since core members also benefit from exchanging with the periphery, managers can now reinforce this mutual relationship to improve the overall innovative performance of their communities. Furthermore, when managers in offline settings need new insights, they should also focus on those experts in contact with the periphery. The findings are highly likely to hold in offline communities of expertise as well, since online communities provide many social mechanisms which can be transferred to offline organizations (Faraj, Jarvenpaa, & Majchrzak, 2011).

Whereas the first essay contributes to the ideation and product development stage of the innovation process, the second essay covers issues at the product introduction stage. Using data from an online scenario experiment, a pre-adoption survey, actual field data and a post adoption survey, the second essay offers several implications to the emerging theory on consumer resistance to innovation (Talke & Heidenreich, 2014). First, the essay identifies a relevant marketing strategy we call evening-out inferior performance using established technology (EIPET). We show that EIPET weakens the influence of passive resistance on the consumers' adoption intentions. EIPET hence is an effective remedy against passive resistance to innovation (Heidenreich & Handrich, 2015). Second, using mental accounting theory (Kahneman, 1992; Kahneman & Tversky, 1979) the essay provides a deeper understanding of the underlying reasons for the success of EIPET. We point out analogies to flat rate bias research (Lambrecht & Skiera, 2006) and show that the insurance effect and the overestimation effect apply as well in the RDI adoption context as they have been shown to apply in the tariff choice setting. Third, by delineating the parallels which exist between the strategy of offering a flat-rate and EIPET in innovation adoption, the essay contributes a new aspect, in the form of a bias, to theory on radical and disruptive innovations (Chandy & Tellis, 1998; Christensen, 2016) we call radical disruptive innovation modification bias (RDIMB). The RDIMB is given when (1) companies introduce a further alternative to consumers'



choice set which is functionally superior and (2) the surplus in terms of functionality is actually unneeded, but does not lead to dissatisfaction or negative word of mouth in the post-adoption phase.

When introducing RDIs, managers should enlarge the consumers' choice set with a functionally superior modified version using established technology to increase the adoption intentions of those consumers who would completely defer their choice and stick with the default otherwise. Furthermore, managers should allocate a significant share of the overall production capacity to producing the version of the RDI with the additional functional feature. During production planning, managers should consider that consumers will prefer the modified version of the RDI. Managers applying EIPET can count on a RDI modification bias in the long run such that there seem to be no rebound effects from consumers' post-adoption experience. Consumers are not less satisfied with the product although they do not need its functional surplus from an objective perspective. Hence, EIPET grants mutual benefits to the firm, in terms of an increase in consumers' adoption intentions, and to the consumers, in terms of products which suit their long-term needs.

The contributions of the third essay are relevant to the diffusion of innovations. Using data from a longitudinal post-adoption survey, the essay offers insights regarding customers' attitude formation process. The essay makes several contributions to theory about the role of consumer innovativeness (Bartels & Reinders, 2011) and product form for product innovation adoption decisions (Hoegg & Alba, 2011; Truong, Klink, Fort-Rioche, & Athaide, 2014). First, we demonstrate that aesthetic product value is strongly relevant to innovative consumers in the post-adoption phase. The influence of aesthetic product value on attitude toward the product is stronger for consumers with high levels of the psychological trait innate innovativeness. Second, the essay reveals that there is a halo effect of product aesthetics (Chitturi, Raghunathan, & Mahajan, 2008; Creusen & Schoormans, 2005; Hoegg & Alba, 2011) in the post adoption phase such that consumers assign less weight to their own objective usage experience when they like the products' visual aesthetics better. Third, the essay investigates the interplay of innate consumer innovativeness and aesthetics (Hoegg & Alba, 2011) and shows that a halo only exists for experienced hedonic utility when consumers are characterized by high levels of innate innovativeness.

Managers should actively co-create product forms with potential customers to generate aesthetics that those consumers will fall in love with over time (Hoyer, Chandy, Dorotic, Krafft, & Singh, 2010). Co-creation workshops focusing on optimizing aesthetic value will be most effective when customers are highly innovative, because managers can create the halo effect on experienced hedonic utility for these customers.

## 5.2. Limitations and Further Research

This dissertation has several limitations which need to be addressed to clarify the generalizability of the findings. The limitations open up avenues for further research in the field of marketing and innovation.

Essay 1, investigating the core-members' benefit from talking to the periphery in online innovation networks, provides the opportunity to look more closely at specific characteristics of peripheral members. Dahlander and Frederiksen (2012) showed that the periphery is the place where cosmopolitans, i.e. members which are part of different communities at the same time, are located. Hence, further research could distinguish between the core members' exchange with cosmopolitans and non-cosmopolitans. Furthermore, netnography could be applied to identify peripherals which are lead users (Kozinets, 2002). Both, the core members' exchange with cosmopolitans and with lead users, could have a positively moderating influence on the increase in expert influence they receive from talking to peripherals. Furthermore, research could investigate innovation forums which use gamification elements to motive core-periphery interactions. Does core-periphery exchange also lead to an increase regarding expert influence when motivation is extrinsic? Moreover, further research could use different conceptualizations of the network core. Whereas this dissertation used an algorithm for leveraging the social proximity between members to identify the core, the core community could also be viewed as an organization within the social network. In the latter case, the core would be defined via membership roles.

Concerning essay 1, there is furthermore a need to investigate the process between the core members' exchange with the periphery and its connectivity in the core more carefully. As mentioned, I only approximated mindfulness using the reach of core members in each period. However, mindfulness also could be directly measured using text mining approaches, sentiment analysis and content analysis. An alternative operationalization would also allow capturing different facets of mindfulness.

The findings of essay 2 are limited regarding their generalizability. Further research could rule out that EIPET also works regarding continuous innovations. So far, the insights obtained in the four empirical studies are all based on the example of the BMW i3 electric car, which is a radical and disruptive innovation. The focal innovation in essay 2 was an electric vehicle and the additional feature extending its range was a small combustion engine working like an emergency backup generator when needed. Hence, further research could investigate if a modification bias also arises when the focal innovation is not disruptive, meaning inferior compared to existing products, but only radical such that it represents totally new technology, to rule out this possibility. Furthermore, research could investigate if disguising a radical innovation as continuous can also be an effective means to overcome consumers' resistance to innovation. The significance of the convenience effect, meaning consumers' tendency to stick to what they are already familiar with, suggests that familiarity potentially could also be achieved via changing the products' appearance, such that it becomes more comparable to products consumers already know and thus help to overcome uncertainties.

Furthermore, the RDIMB in essay 2 implies that in terms of post-adoption product usage, customers who purchased the version of the product with the functional surplus do not differ from customers who adopted the basic innovation. However, product usage is multidimensional and users continue to explore new ways to use products throughout the product life-cycle (Shih & Venkatesh, 2004). Hence, the hypothesis that both customer groups do not differ in their post-adoption product usage was only tested regarding the primary purpose of the feature, which exists in extending the drivers' range. Although we did not observe statistically significant differences between both groups, the model comparison between driven distance per trip and per day hints that the RDIMB potentially is not that strict as the flat rate bias, which exists in a clear overestimation of consumers' needs at all times. There are absolutely no differences between both groups in the model predicting distance per trip (see Table 19), but as shown in Table 20, the grouping factor turned out to be marginally significant ( $p < .10$ ) in the first regression model predicting the log of driven distance per day. Hence, on average the feature is clearly unneeded - but there may be very seldom days where customers who purchased the feature make use of it to drive a greater distance.

Building on essay 3, further research could compare different product forms to investigate if there is a certain aesthetic principle that accounts for the halo effect in the

pre- and post-adoption phase. In the essay, we used the within-variance of a single product form. When researchers systematically vary the between-variance instead, they could identify product forms which are more likely to cause a halo effect than others. We also differentiated between experienced hedonic and functional utility. Furthermore, research could test if innate consumer innovativeness also moderates the halo effect in the pre-adoption phase. We showed that this personality trait interacts with the consumers' aesthetic evaluations in the post-adoption phase, such that the halo effect only exists for highly innovative consumers. Innate consumer innovativeness could also positively moderate the influence of anticipated product fun on adoption intentions.

Finally, essay 3 used a panel approach to identify the causal effects in the complex interplay of experienced utility, aesthetic value, innate consumer innovativeness and attitude toward the innovation. As mentioned, due to the small temporal distance between the survey waves of approximately 3 months, the observed changes in the within-variance are small, as expected. Further researchers could set up panel designs with greater temporal distances between waves to obtain additional within-variance and to improve our understanding of the long term effects throughout the products' entire life-cycle.

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