Fakultät für Wirtschaftswissenschaften

Lehrstuhl für Marketing und Konsumforschung

Improving Consumer Choices using Dynamic Feedback on Digital Devices

Bernhard Mohr

Vollständiger Abdruck der von der Fakultät für Wirtschaftswissenschaften der Technischen Universität München zur Erlangung des akademischen Grades eines Doktors der Wirtschaftswissenschaften (Dr. rer. pol.) genehmigten Dissertation.

Vorsitzender:	Prof. Dr. Michael Kurschilgen
Prüfer der Dissertation:	1. Prof. Jutta Roosen, Ph.D.
	2. Prof. Dr. Helmut Krcmar

Die Dissertation wurde am 11.04.2019 bei der Technischen Universität München eingereicht und durch die Fakultät für Wirtschaftswissenschaften am 15.08.2019 angenommen.

Acknowledgements

Ich danke Frau Professor Jutta Roosen für die Möglichkeit, meine Dissertation an ihrem Lehrstuhl zu schreiben. Besonders bedanken möchte ich mich für die geduldige Unterstützung bei der Konzeption der Experimente sowie deren Auswertung und Veröffentlichung.

Beim gesamten Lehrstuhl-Team möchte ich mich für den freundschaftlichen Umgang und die kollegiale Unterstützung bedanken, besonders im kleinen Büro.

Für die Unterstützung des Projekts "optimale Verbraucherinformation" danke ich dem Bayerischen Landesministerium für Umwelt und Verbraucherschutz sowie unseren Projektpartnerinnen von der HSWT, Frau Professor Mirjam Jaquemoth und Sandra Albertsen.

Im enable Cluster möchte ich allen beteiligten Professoren, Nachwuchswissenschaftlern und Industriepartnern für den regen Austausch und die interessanten Gespräche danken, insbesondere Herrn Professor Klaus Menrad und Frau Minh Nguyen.

Herrn Professor Helmut Krcmar danke ich für die Übernahme des Zweitgutachtens und Herrn Professor Michael Kurschilgen für den Vorsitz der Prüfungskommission.

Ein großer Dank an Andrea und meine Eltern.

Summary

Consumer choices are crucial to some of today's most severe problems, especially in the context of environmental and health behavior. Therefore, this dissertation investigates how consumer choices on energy and food can be improved with the help of digital devices. To do so, different forms of dynamic feedback and selected other measures were tested in two laboratory experiments in Germany, concerning their ability to improve choices in the process of consumer interaction with digital devices. Applications are a smart electricity meter in the context of environmental relevant behavior and a digital fast food ordering screen in the study of health behavior.

In experiment I, consumers had to choose between different setups of smart electricity meters. It was found that the features at stake differed considerably according to how much consumers liked them. The following list shows these features in descending order concerning how much they were valued: (1) The possibility to benefit from a reduced electricity price in times of high net load due to an interconnection between smart electricity devices and the electricity provider, (2) an optical signal following the same purpose, (3) different setups of electricity consumption displays, and (4) enhanced data protection. The experiment found a negative value attached to radiation produced by the smart meter.

In experiment II, dynamic feedback was integrated in an order terminal in a fast food environment. Feedback elements were an order assistant in the form of an animated face and a display using traffic light colors, both instantly reacting to the amount of calories in the shopping basket. The elements were conceived to address young adults and to lead to lower calorie choices. The third element following the same goal was highlighting low calorie menu items. The order assistant was found to be the only element significantly reducing calories ordered while this effect only could be observed for female participants. Also, several moderating psychophysiological variables were identified.

Findings of both experiments show considerable potential of the tested measures and can help to improve the setup of future smart electricity meters and fast food order terminals. More generally speaking, this thesis contributes to the understanding of how consumer information provision can be improved using digital devices.

List of Contents

List of Tables

List of Figures

List of Abbreviations and Acronyms

AI	artificial intelligence
AOI	area of interest
BMI	body mass index
CBA	cost benefit analysis
et al.	et alii
e. g.	exempli gratia
DGE	Deutsche Gesellschaft für Ernährung (German Nutrition Society)
DCE	discrete choice experiment
ICT	information and communications technology
i. e.	id est
iMSys	intelligent measurement systems
RQ	research question
Kcal	kilocalories
kWh	Kilowattstunde
R.U.T.	random utility theory
vzbv	Verbraucherzentrale Bundesverband
WTP	Willingness to pay

List of Appendices

1. Introduction

Over the last decades, the amount of goods that consumers can choose from increased dramatically. There are several reasons for this development. Ever larger supermarkets and shopping centers literally gave room for new products and product categories as well as product diversification. The spread of personal computers, smartphones, tablets and smart speakers as Google Home or Amazon Alexa are not only new product categories, but made it possible to shop online anytime and anywhere. This increasingly complex choice environment is a challenge for consumers and consumer information policy alike. Consumer information, especially that from neutral sources, can help consumers to improve their choices and prevent them from bad ones. However, consumer information provision faces some challenges, especially against the outlined background of ongoing digitalization and an increasing information overload. This thesis contributes to solving these challenges.

1.1. Background

As consumer choice is in the very center of this doctoral thesis, some introductory remarks on the topic are necessary. Whenever a choice for a product or service is made, it can be assumed that this is preceded by some sort of cognitive effort on the side of the decision maker. Sometimes this is a rather complex process where a number of influencing factors are being considered, e. g., when a decision is to be made on the mode of transport to get to the airport. The modes of transport under closer consideration for the described choice situation may depend on factors such as the available budget, luggage size, the expected amount of traffic and previous experience with some of these modes of transport. In cases where a decision is hard to make, some consumers may take additional steps by weighting the pros and cons for their favorite modes of transport. Other consumer choices are made in a less effortful and conscious way, e. g., when choosing a dish and side dish for lunch.

It is common sense that routine choices as the one for a side dish in a cafeteria are made with relatively little effort also because in cases where they turn out to be suboptimal, relatively little harm is produced. To remain with the upper examples, a side dish that tastes bad is surely less painful than missing a flight.

This differentiation between an effortful, conscious way of decision making and an automatized way of making choices is of importance in this doctoral thesis because it can determine how consumer information should be framed. Before coming back to this topic, the upcoming paragraphs will shed light on the issue of consumer information and the challenges that can arise with its provision.

When consumers are to make an informed choice for a product or service from a range of available alternatives, they necessarily need some sort of information to do so. For the purpose of this dissertation, consumer information is distinguished according to two criteria, namely source and intended effect. Concerning sources, there are (1) commercial information sources such as advertisement, (2) peer information such as reviews and opinions on e. g., Amazon and (3) consumer information provided by the government or government-related authorities. For (1) and (2), the consumer cannot be sure if the information is neutral and trustworthy. By contrast, (3) can be seen as a complement and correction of suppliers' information policy (Kuhlmann, 1990, p. 9) as it is independent from producers' and retailers' attempts to shed positive light on their products. This distinction illustrates why neutral consumer information is essential to enable informed consumer choice.

This dissertation further distinguishes two intended effects of consumer information, namely (1) changing the mindset of the consumer so that future choice outcomes are altered or (2) providing feedback and other measures as nudging in the process of decision making to improve immediate choice outcomes. Figure 1 points at this distinction between (1) traditional consumer information and (2) new consumer information.

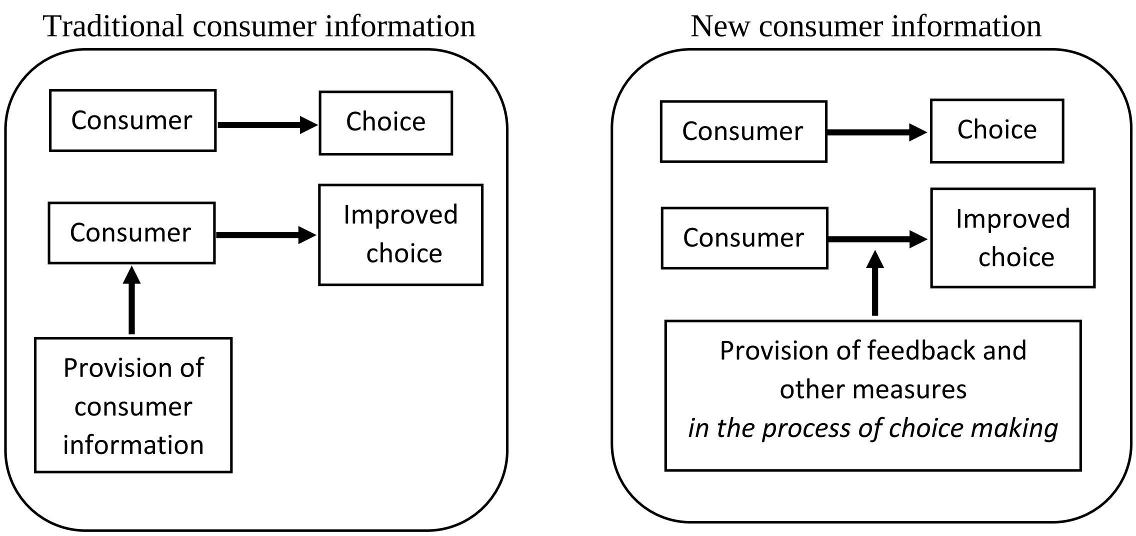


Figure 1: Difference between traditional and new forms of consumer information

What was called traditional and new consumer information above use different measures to change consumer choice while they both aim to do so by providing information. Traditional consumer information is thought to be all kinds of information on products and services e. g. in written form, on TV or online. The term ‘traditional’ is used as providing consumers with information and in this way has been applied in consumer policy for a long time. Kuhlmann (1990), distinguishes consumer education, consumer counselling, consumer information and consumer awareness (see also chapter 2).

The term ‘new consumer information’ was chosen in analogy to the term ‘new economy’, which is constituted by a shift from machine-focused technology to human-focused-technology (Cooke, 2001). The new economy turned the hitherto production economy into a knowledge economy (Kim & Mauborgne, 1999). A similar transition can be traced in the field of consumer information provision, away from the focus on a physical product towards more human-focused forms of consumer information.

All consumer information falling under the latter, ‘new’ category, use insights from behavioral economics to change consumer behavior, e. g., by deliberately changing the choice architecture, meaning the situation in which choices are made (Thaler & Sunstein, 2008, p. 6). Behavioral economics build on the premise of a large number of suboptimal routine choices that individuals make every day producing harm on the individual as well as societal level (ibid.). A prominent example is excessive meat consumption causing cardiovascular diseases as well as a large amount of carbon dioxide from animal production in western societies. As many consumers already are aware of the negative consequences of their behavior, an increase in the provision of traditional consumer information on this topic will in many cases not help them to change their routine food choices.

This does not mean that what was called traditional consumer information is inefficient. For example, previous literature found a positive correlation between schooling and good health where it was shown that schooling leads to healthier lifestyles through improved health knowledge (Kenkel, 1991).

Another challenge for contemporary consumer information provision and policy is related to the constantly growing amount of products and services consumers can choose from. The constant update and adjustment of respective consumer information poses a problem to the institutions providing consumer information due to their limited resources. Also, the large amount of products to choose from & respective information can be confusing for consumers. While offering an increased amount of new as well as traditional consumer information, especially online, can help to tackle this challenge, it is especially traditional consumer information that may increase injustice as it needs to be searched for, processed and applied. Consumers are more likely to do so successfully the more well-educated they are. This situation increases the gap between well-educated, wealthy consumers and those with less education and income as it improves consumer choices only of the first group, which has been more affluent in the first place.

1.2. Problem statement and outline of the thesis

This doctoral thesis aims to contribute to the understanding of the effects of information provision to improve consumer decision making using the possibility of interactive and dynamic information feedback. It also addresses the named challenges or problems of consumer policy mainly by using dynamic feedback on digital devices. The chosen measures fall under the category of new consumer information. Information instruments are tested in the context of energy choices (i. e., electricity meters in private households) and food choices (i. e., order terminals in fast food restaurants). The thesis is based on an experimental paradigm. Figure 2 shows which measures were used in the two experiments of this dissertation.

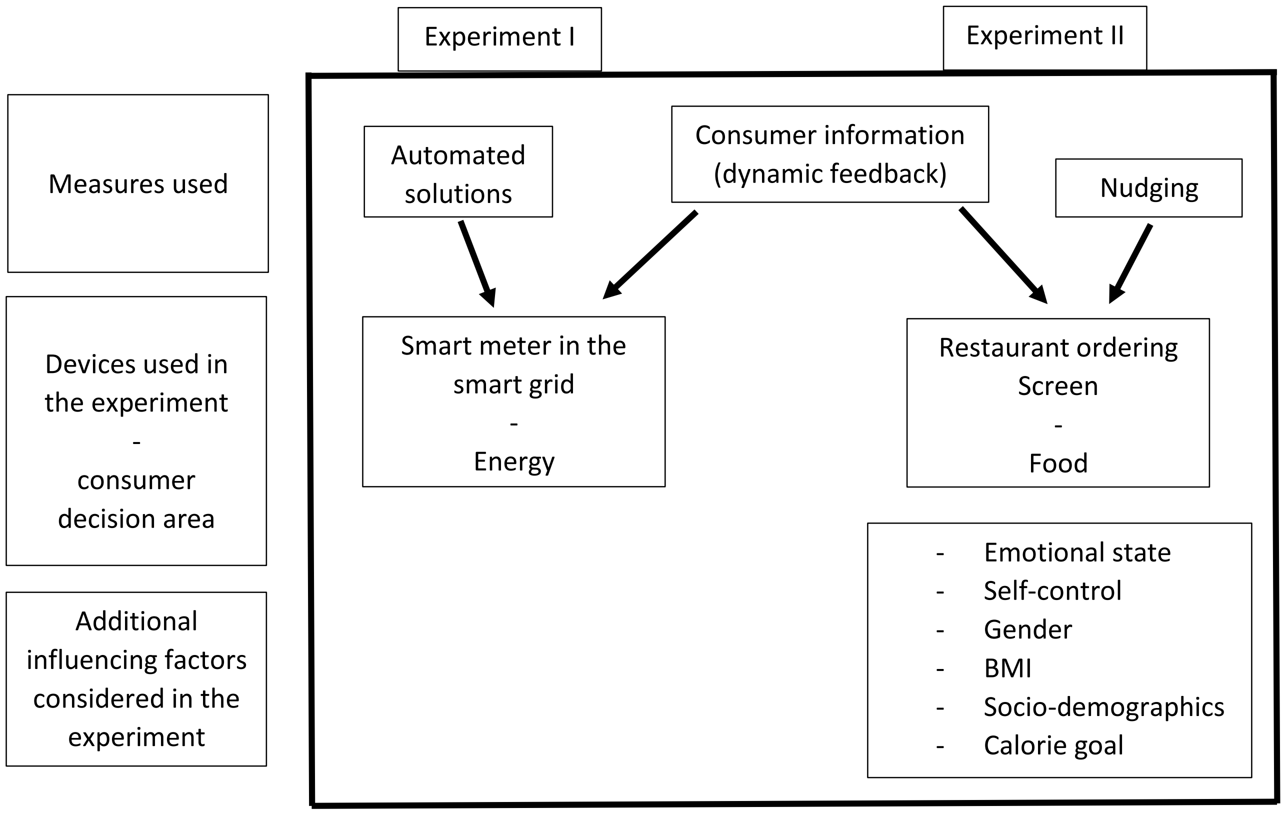


Figure 2: Topics and measures of dynamic feedback in this thesis

Source: Own illustration

In experiment I, consumers reveal hypothetical choices of different setups of smart electricity meters in the context of a smart grid. In a hypothetical choice experiment, electricity meters are described by various attributes including their potential to use information from the grid to manually or automatically control electricity using devices. Some of these provide the user with dynamic feedback on his or her electricity consumption, others involve automated solutions for smart household devices in combination with feedback from the smart grid.

Consumer information in the form of dynamic feedback is also central to experiment II where it is applied on a restaurant ordering screen as feedback on the amount of calories that are currently in the shopping basket. Different ways of communicating this (numerical) information are tested with regard to their impact on choice.

The three essays forming this thesis have a joint focus although they rely on two different experiments (essay I presented in chapter 4 is based on data collected in experiment I, essays II and III presented in chapters 5 and 6, respectively, are developed using data collected in experiment II). The joint focus of the experiments is to which extent choices can be improved when consumers interact with digital devices. The crucial point being that digital devices have several advantages over common means to provide consumers with information: They can provide feedback that is dynamic, i. e., temporally adjusted or personalized to different choice situations or users. The topics of energy and food were chosen due to their high relevance for sustainable consumption as it will be outlined in chapter 2.4. While experiment I addresses the choice of an information tool (with or without dynamic feedback), experiment II addresses the question of how dynamic feedback matters for subsequent choices using this tool.

The outline of the thesis is as follows: Chapter 2 gives an overview of relevant facts on consumer information policy and especially on consumer information against the background of digitalization. It is arranged in chronological order, starting with an historical overview of the topic, introducing current consumer information (policy) measures and actors. It concludes with subchapters on the influence of digitalization on consumer information and types of consumer decision areas. Chapter 3 provides a theoretical framework by elaborating on research on decision making and research on consumer information in two subchapters.

This is followed by essays I, II and III in chapters 4, 5 and 6, respectively. Chapter 7 discusses the overall results and elaborates on implications and limitation while chapter 8 gives an overall conclusion.

2. Consumer information (policy) – past to presence

The consumer bill of rights from 1962 where John F. Kennedy defined a set of consumer rights can be interpreted as the birth of modern governmental consumer policy in the United States. The consumer rights he proclaimed are the following:

- The right to safety, especially concerning health hazards from defective products
- The right to be informed truthfully by producers
- The right to choose which emphasizes the downsides of monopolies for consumers and therefore guarantees free market entry for suppliers of consumer goods
- The right to be heard, i. e., a guarantee that consumer rights against providers of consumer goods can be utilized. This right also includes the participation of consumer representatives in decisions concerning economic policy (Kuhlmann, 1990, p. 10).

A major government-initiated consumer policy measure in Germany was the foundation of the state-funded independent consumer organization donation product test (Stiftung Warentest) on the initiative of chancellor Ludwig Erhard in 1964, which had its forerunners as early as in 1903. Since then, the catholic housewives' union (Katholischer Frauenbund), which still exists today, provided information and advice on various topics for its members (Breuer, 1998, p. 163).

In contrast to contemporary consumer policy in Germany, the consumer bill of rights and the actors of the earlier so-called consumer movement had its main focus on protecting consumers from faulty or defective products (Kennedy, 1961). Following this dogma, policy makers all over the world have since then installed a system to ensure that products meet strict safety standards before they enter the market. This is especially true for Europe, where, in contrast to the US, protection measures are explicitly taken as early as possible (Windhoff-Héritier et al., 1996, p. 242). Besides protection from faulty products or false information by producers, contemporary consumer policy also aims to actively inform the consumer, not only for the sake of protection but so that s/he can make informed choices, as will be shown in the next subchapter.

2.1. The responsible consumer and its influence on contemporary consumer policy

In the German system, the concept of the responsible consumer (mündiger Konsument, Reisch, 2003) reflects the notion of a consumer actively searching for information to make informed choices which is fundamentally different from one who is only in need of protection. To be more exact the responsible consumer is a so-called role model that was brought up by German policy. The definition of role models has frequently been used in Germany from the 1960s onwards to "define codes of conduct (…) where passing laws would not make sense as they could not be enforced" (Schwan, 2009, p. 51). Role models are also called "weak controlling tools" (ibid., p. 17). In the case of the responsible consumer, it is the problem of a large amount of stakeholders aiming to influence consumers in contemporary society that is meant to be addressed.

In the English literature on the topic, the term "mature consumer" is mainly connoted to age, e. g., those consumers aged over 55 (Laukkanen et al., 2007). For this reason, the author will only use the term "responsible consumer" in the following. The responsible consumer is a prerequisite, and also the result of successful consumer policy (Reisch, 2003, p. 9). S/he sets priorities, uses his or her income wisely to make the appropriate choice of consumer goods to increase quality of life. The definition also includes self-organization ability and responsibility (ibid.). Previous literature focused on numerous aspects of responsible consumption such as sustainability (Lange, 2008), socially responsible consumer behavior (Ha-Brookshire & Hodges, 2009) or environmental responsibility (Follows & Jobber, 2000). Another important issue is to strengthen the "activation of the ability to act on one's own responsibility" (Müller & Mackert, 2003). The goal of consumer policy is to influence consumers towards this utopia (Kuhlmann, 1990).

However, role models change over time. In 2010, the scientific advisory board of the Federal Ministry for Nutrition, Agriculture and Consumer Protection (BMLEV) asked for a higher degree of differentiation when discussing consumer role models (Micklitz et al., 2010). They suggest three ideal consumer types: The trusting, the vulnerable and the responsible consumer of which only the latter was mainly characterized by the need of education and information, whereas the trusting and especially the vulnerable consumer are also in need of special protection. This line of thinking is also reflected in the recent coalition agreements of the German government. In 2005 (legislative period 16), it explicitly stated that the responsible consumer is its underlying role model. Consumers need to be informed in a way that s/he can decide and choose on his or her own (CDU, CSU, & SPD, 2005, p. 129). The coalition agreement from 2009 (legislative period 17) states that their role model is the well-informed consumer who is capable of self-determined action and responsible. This role model calls for more consumer education as well as transparency, awareness and law enforcement, but also more rights, where necessary (CDU, CSU, & FDP, 2009, p. 44). The coalition agreement from 2013 (legislative period 18) does not elaborate on a role model when it comes to consumers but it states that consumer policy is based on a differentiated notion of consumers. Consumers should have the opportunity to decide on their own and be provided with information, counseling and education. However, in cases where they cannot protect themselves, the government is to provide protection. The digital world and the financial markets are mentioned as examples (CDU, CSU, & SPD, 2013, p. 124). This is not a coincidence as public attention on consumer protection especially in the field of banking increased under the impression of the financial crises and its effects on private assets starting with the Lehman-crises in 2008. The latest coalition agreement from 2018 (legislative period 19) also does not mention a specific consumer role model, but it stresses the importance of consumer protection when it comes to digital products and services. The role of consumer information and counselling is strengthened by the installation of a nationwide and uniform consumer portal called consumer pilot (Verbraucherlotse), which is to cooperate with existing institutions and authorities (CDU, CSU, & SPD, 2018, p. 134). Even though the exact term is not explicitly mentioned in the most recent coalition agreements, the responsible consumer remains an important concept of consumer policy in Germany.

2.2. Consumer policy measures to influence consumer choices and behavior

Traditional consumer policy instruments can be distinguished into four categories. This categorization was made for the first time by Scherhorn in 1973. Other authors including Biervert et al. (1977) and Kuhlmann (1990) used it with slight variations (Gottschalk, 2001, p. 160). The latest categorization by Kuhlmann distinguishes consumer education, consumer counselling, consumer information and consumer awareness.

Consumer education aims at changing attitudes, needs and behavior especially of youth and young adults (Kuhlmann, 1990, p. 9). Typical actors involved are general schooling and adult education institutes (e. g., Volkshochschule). Consumer counselling aims at providing a solution to a concrete issue that an individual consumer faces, typically in personal contact with a professional counsellor in consumer centers (Verbraucherberatungsstellen, Kuhlmann, 1990, p. 304ff). The term consumer information includes all material that is suitable to satisfy consumers' need for information when she/e wants to make an informed decision for a certain product or service. Only when the respective piece of information comes from a trustworthy source, e. g., consumer centers or the magazine test of the Stiftung Warentest, it can be described as a complement and correction of suppliers' information policy (ibid., p. 9). All public awareness-raising campaigns or other measures aiming to cause or reinforce certain behaviors in society fall under the term consumer awareness. Typical actors are (Federal) Ministries funding these campaigns.

2.3. Information and digitalization

As this thesis deals with consumer information as a policy instrument in the age of digitalization, this section will further look into the link between consumer information and digitalization. Previous research identified digitalization and related issues as the main societal transformation of their times as early as in the 1970s (Beniger, 1986, p. 4). Some examples of what was thought to be a fundamental dynamic in the respective year is listed in the following: Computerized society (1970), age of information (1971), information revolution (1974), information economy (1977), network nation (1978) or computer age (1979) (ibid.). Lehdonvirta (2012) claims that "the digitalization of consumer culture" started with the first online retail sites in the 1990s. Publications dealing with more recent consumer-related developments in this field focus on many different issues such as the interactivity that comes with digitalization and its effect on consumer satisfaction in online retailing (Ballantine, 2005, Liu et al., 2008).

For the purpose of this dissertation, the goal is to see the bigger picture and therefore to take a historical approach to the digital environment that consumers find themselves in today when searching for consumer information. The assumption behind this course of action is that the digitalization of consumer information and other aspects of everyday life can only be understood by examining how it evolved.

Consequently, a three-phase model of digitalization will be introduced, starting with the digitalization of media in the 1970s with the first personal computers. This first phase of digitalization still goes on today with the digitalization of antique documents with the help of 3D scanners in libraries (Cubaud et al., 2005). Following Hagberg et al. (2016), the second and third phase of digitalization are called "the digitalization of the retailer-consumer *relationship* on platforms" and "the digitalization of the retailer-consumer *interface* on new devices*",* respectively. In the following, for each phase, present and past impacts of digitalization will be outlined on the way in which consumers are provided with information and on how information is accessed by consumers.

2.3.1. Phase 1 - Digitalization of media

The term information and communications technology (ICT) is closely linked to the topic of this thesis: It is the mass diffusion of ICTs in everyday life that makes digitalized information easy and fast to access in comparison to former times when information was only available in printed form. Some examples of ICTs are: Web logs (blogs), word processors, video editors, world wide web browsers, web editors, e-mail, spreadsheets, presentation software, instant messaging, plug-ins for web resources, listservs, bulletin boards, avatars, virtual worlds (Leu Jr et al., 2004). While this summary only lists the software side of ICT, the respective hardware (personal and tablet computers as well as mobile phones) is of equal importance as the information is accessed through these devices. Both the hardware as well as the software underwent considerable changes over time that also had an impact on consumer information in terms of access, provision and use. The first digitalized media were photographs of newspapers and book pages stored on microfilm. It could not easily be accessed from home via word processor and/ or worldwide web browser but only via microfiche reader in libraries or companies.

Figure 3: Microfiche reader in library

Source: Wikimedia

Advantages of information on microfilm are easier accessibility compared to printed newspapers or books. Distances in the archive of microfilms are smaller and films are less heavy to carry than books. In addition, digitalized information is more durable than printed one, when stored properly. What was not yet possible with microfiche devices is full text search, meaning that words or phrases can be searched for in the ICT system. In the 1970, the number of personal computers started to increase. This lead to more and more information being digitalized in libraries, communities and companies. The increasing distribution of personal computers in private households from the 1980s on led to an increasing ICT literacy in an increasing share of society. But only an increasing share of private households having an internet connection at home made the developments that were traced so far relevant for the diffusion of consumer information. Now it was not only possible to search for the desired information in full texts, internet access literally brought the world's knowledge to private homes, making knowledge, a public good (Rich, 1997).

Another feature of the internet that is of great importance especially for the issue of consumer information is the ease with which information can be published. Once the critical mass of internet users publishing information in forums was reached, a new source of relatively neutral and unfiltered consumer information was born. In forums, everyone can exchange observations and opinions without a third party involved except of the supposedly neutral provider of the forum. Previous research named this online collection of statements of subjective information about products "electronic word of mouth" (Lis & Neßler, 2014).

The described developments led to more consumer information being available, not only as it was easier to access but also due to no or low publishing costs. This theoretically makes it more likely that every consumer finds the piece of consumer information that fits his/ her needs. In practice, however, especially due to consumers' low willingness to pay for information online, its quality and up-to-dateness largely varies which can lead to confused consumers and information overload. To sum up, phase 1 of digitalization led to a massive increase in the amount of available consumer information. Diversity and the degree of specialization increased especially due to activities in forums while information quality did not necessarily increase.

2.3.2. Phase 2 - Digitalization of the retailer-consumer relationship on platforms

The second phase of digitalization of consumer information, as this thesis frames it, started with the rise of the first online-retailers as Amazon.com, Inc. which was founded in 1994. Three years later, in 1997, it claimed to be the world's largest bookstore (Graf & Schneider, 2016) which illustrates its immense growth rates. The crucial point of this development is that Amazon brought consumer information in the form of product reviews to a new level in several respects. Compared to the forum activities described before, product reviews are more easily accessible for almost any (type of) product, they are also comparatively trustworthy due to their large number which makes it rather unlikely that fake statements have a large effect on the overall judgement. Also, sites as Amazon and Booking.com claim to make sure that only those who really bought the respective product or booked the respective hotel can write a review. There is no doubt that electronic word of mouth as product reviews considerably impact sales (Chevalier & Mayzlin, 2006). Previous work focusing on the German market frames trust in electronic word of mouth as a complex issue depending on numerous factors (Lis, 2013).

However, platform sites selling products as Amazon, but also those selling services as Booking.com, Uber or MyHammer improved the situation of consumers as they made word of mouth more accessible and transparent. This is due to their clear and appealing way of presenting it, which is a big advantage in comparison to former forum activities with many topic folders and subfolders where relevant consumer information was hard to find in some cases.

Problematic is the current trend of a handful of American global players constantly gaining market share which creates the threat of social media monopolies with serious consequences for the plurality of voices and objectivity of (consumer) information (Gehl, 2013). The near future will show if this trend continues or if the market can heal the current unfavorable developments. Another solution would be legislative interventions to ensure that monopolies do not put the advantages of digitalization of consumer information in danger.

2.3.3. Phase 3 - Digitalization of the retailer-consumer interface on new devices

What already began in phase 2 with the improvement of user interfaces for finding product reviews and other consumer information on online platforms, has reached a next level with the development of new consumer devices. They provide convenient services that make it easier to judge product qualities, product alternatives and market prices. The respective devices consist of innovative hardware that is mass-tailored to new services. They are designed to make specific domains of everyday life easier or provide it with new services and/ or information. There are not yet many of these devices on the market but their (future) potential disruptive impact cannot be underestimated, also and especially as an information tool to make relevant consumer information more accessible. Two of such devices are experimentally tested in their ability of doing so in the essays of this dissertation.

Hagberg et al. (2016) called the described developments the digitalization of the retailer-consumer interface. They frame digitalization as "integration of digital technologies into everyday life by the digitization of everything that can be digitized" (ibid.). In the following, an explanation will be given for how the new devices can do so. It is no coincidence that their development falls under a general trend of interconnecting devices in local networks or the internet, the so-called internet of things. The terms was used for the first time in 2002 at the Massachusetts Institute of Technology (MIT) (Abicht & Spöttl, 2012, p. 29). It can be defined as the combination of technologies from different domains to a system that is geared to application. Networks can be characterized into three degrees of interconnectedness:

- bilateral networks, the most primitive stage is a connection between two objects
- local networks describe locally or technically closed systems
- global networks are connected via the internet or mobile networks. In these open networks, the participating devices can be distinguished according to their unique IP-addresses (ibid., p. 19).

Artificial intelligence (AI) can be seen as the next evolutionary fourth phase of digitalization. Not only is its progress based on the large amount of data acquired in the previous stages of digitalization as described before. The fact that AI can structure and analyze big data for key insights automatically (O'Leary, 2013) resulting in "knowledge" that is represented as semantic networks (Brodie et al., 1984, p. 76) created speculations about AI ending in a digital version of the human brain someday (Dreyfus & Dreyfus, 1991). Only the future can show whether or not this can be achieved, meaning if the fourth phase of digitalization ends with the creation of a self-conscious super-intelligent computer.

Surely, artificial intelligence at a much lower level, already has considerable impact on consumer products and information due to the integration of increasingly intelligent and autonomous functions in devices as vacuum cleaner robots, self-driving cars or Google's increasingly intelligent search algorithms. These developments will probably go on with contributing to make consumer information more available and more personally relevant. They may also lead to new information tools, i. e., devices that – besides making life easier - make consumer information more available. Again, only the future can show to what extent and in which decision consumers areas are willing to use new digital information tools in everyday life.

2.4. Types of consumer decision areas

2.4.1. Overview

Products and services can be divided into different consumer decision areas. People buy clothes, consumer electronics, cars, have the car repaired from time to time or have a haircut. They also buy the electricity they use every day, groceries or go to a restaurant. This list could randomly be extended while it is also possible to sort consumer goods and services in an orderly and hierarchical way. For example, going to a restaurant and buying groceries both match into to the consumer decision area of food, while deciding for an electricity provider, buying a fridge or having solar panels installed on one's roof belong to the domain of energy. In the following, the special relevance of the consumer decision areas of food and energy will be outlined as these were chosen for essays I (energy), II and III (food). These consumer decision areas were also chosen because they are especially suitable for several reasons to deliver consumer information on digital devices.

2.4.2. Energy

The consumer decision area of energy which was chosen for essay I of this thesis as it is closely linked to anthropogenic climate change being one of the most severe problems of humankind (Liao et al., 2012). Related consumer decisions are energy saving behavior, the choice of (energy efficient) household devices or choosing an electricity provider (producing electricity from renewable energy sources). The consumer decision area of energy involves a large number of behaviors that are desirable from a consumer policy point of view which makes it an ideal topic for the purpose of this dissertation, namely testing how related consumer information can be made more available. As this doctoral thesis focuses on digital devices using dynamic feedback, the consumer decision area of energy has another advantage over other consumer decision areas. The technical complexity it involves makes it reasonable for consumers to use a smart electricity meter to make the related complex information involved more available.

2.4.3. Excurse: The German energy turnaround

An increasingly decentralized energy system with a rising share of electricity generated from renewable sources makes it possible for consumers to involve themselves more actively, which can result in cost savings for consumers as well as producers of electricity. Also, less electricity needs to be produced in this scenario which is only possible when consumers frequently interact with a smart electricity meter. Key is the smart meter's connection to the so-called smart grid which is the network connecting electricity producing facilities and consumers. It is smart due to its ability to communicate with the smart meter and home concerning current net load (Rajagopalan et al., 2011).

For the understanding of the role of net load in the interplay between smart grid and smart home, a short excursion to the energy turnaround in Germany from electricity providers' point of view is necessary. The term net load describes how much electricity the grid currently contains. High net load decreases net stability meaning a blackout or other dysfunctions can occur while a too low net load can lead to blackouts as well (Wang et al., 2015). Net load is fairly easy to control for electricity providers when there is a large share of conventional energy sources involved in producing electricity as coal-fired power stations or nuclear power plants. In times of peak consumption, they can produce more electricity and lower production at night when demand is low. In 2012, the contribution of renewable energy sources to the overall amount of electricity produced was 16.1% and it is expected to rise to up to 30% in 2020 (Deutsches BiomasseForschungsZentrum, 2012, p. 1). This development was made necessary by the political decision to successively reduce the share of electricity from atomic power plants after the nuclear catastrophe of Fukushima in 2011 which goes under the name of energy turnaround (Paatsch, 2016). It leads to severe challenges for net stability in scenarios where (1) much electricity is pushed into the grid by renewable energy sources as wind turbines at times of low electricity demand or (2) when demand is high but simultaneously, e. g., due to no wind, little electricity is produced by wind turbines.

There are several ways to increase the stability of the grid. At times of peak consumption, temporarily switching on conventional energy sources can help to decrease a possible gap to production for the reasons outlined above. Another measure would be storing electricity produced by renewable energy sources in times of low demand to bring it back into the grid when it is needed. The third solution for the problem at hand being of special interest for this thesis involves a short term adjustment of consumers' electricity demand to the current energy production. This works by providing consumers with dynamic feedback on the current net load on their smart electricity meter at home and consumers changing their behavior accordingly (Paetz et al., 2012). They are incentivized to do so with cost savings from a net-load dependent variable electricity tariff. The electricity provider can offer this discount on electricity consumed in times of high net load as a reduction of the gap between electricity produced and electricity consumed means that less electricity needs to be produced or less remains unused, respectively. The electricity producer passes the resulting savings to the consumer to incentivize his/ her behavior.

The smart home concept relating to the concept of the internet of things offers a way to exploit the reduced electricity tariff. To be more exact, it enables saving electricity costs on the consumer side and energy efficiency savings on the side of the electricity producer (Momoh, 2012, p. 178). The smart home concept helps to do so in an automated way, meaning relatively little behavioral change is necessary for the user compared to a non-automated solution. The latter works as follows: At times of high net load, the smart meter receives a signal from the provider indicating that net load is high, via an optical signal at the meter. For the consumer this indicates the possibility to receive electricity for a reduced price which s/he is granted to have an incentive to change his or her behavior. S/he may now decide to consume electricity under the reduced tariff "manually", e. g., by vacuum cleaning or doing the laundry. The automated solution involves smart devices in a smart home. With prior consent of the user, the signal from the electricity provider can automatically switch on devices as washing machine, heating or air condition as soon as reduced price is signaled to the smart meter.

2.4.4. Food

Besides their obviously high frequency in everyday life, food decisions are also highly relevant due to their connection to obesity and related health issues, e. g., cardiovascular diseases (Hubert, Feinleib et al., 1983). They also have a large impact on the environment as the way western countries produce and consume food is unsustainable which leads to reduced soil quality and climate change. Already in 1999 the number of annual deaths due to obesity was estimated at 300.000 (Allison et al., 1999) while it is estimated that 18% of the greenhouse emissions worldwide come from livestock farming (Liao et al., 2012). This links the consumer decision area of food to climate change, which is one of the biggest problems confronting us today (ibid., 2012). Due to this relevance, contemporary consumer policy is relatively active when it comes to package labelling that in the end intends to help consumers to make healthier food choices (Grunert & Wills, 2007).

The complex domain of food is especially suitable for dynamic feedback as it can help to reduce the complexity of the choice situation. An additional reason for the choice of the domain of food in this thesis is that technical devices to order food already exist on the market. Besides the ordering screen chosen in this thesis, there is an increasing number of apps to order food online. Theoretically, the tested means to improve consumer choices also could be applied on these platforms. It is also reasonable to assume that the number of these devices will increase in the future which makes research in this field even more relevant.

Before coming back to the issue of (digital) consumer information, the following chapter 3.1 will elaborate on research on decision making. This is needed for the deeper understanding of the way the experiments performed in essays I, II and III frame consumer information.

3. Theoretical framework

3.1. Research on decision making

Decision making can be defined as making a choice from multiple alternatives. Depending on the underlying paradigm, it is either assumed that the decision maker screens the alternatives according to certain rules to maximize his or her utility (Hwang & Yoon, 1981). This goes under the paradigm of random utility theory (R.U.T.). An alternative approach on decision making assumes that the architecture of a choice greatly influences how people make choices (Thaler & Sunstein, 2008, p. 375). This starting point goes under the paradigm of behavioral economics. More generally speaking, one can distinguish different types of choice situations. There are discrete choices, i. e., choices between two or more alternatives where only one alternative can be chosen. Another case are discrete continuous choices, where the selection of goods is jointly determined by a discrete choice and a conditional continuous choice (Hewitt & Hanemann, 1995). An example for such a situation is when a discrete choice on a menu containing several food items is to be made while the continuous choice for the overall number of calories in the purchase also influences which food items are chosen. As, due to budget constraint, the choice is still made from a finite number of subsets, the resulting approach is a two-stage maximization principle (ibid.).

Such a simultaneous consideration of criteria as calories, price, type of dish (drink, side dish, main dish) also leads to an increase in choice complexity. The same holds true for an increase in the number of choice options and the number of product attributes that the choice maker finds relevant and therefore takes into account when making his/ her decision.

The difference between R.U.T. on decision making and behavioral economics becomes clear here: While R.U.T. assumes that decisions are made on basis of an evaluation of the alternatives at stake, behavioral economics rather focuses on modes of decision-making. By doing so, behavioral economics contribute to explain observable phenomena that were hard to explain within R.U.T., e. g., why complex decisions, i. e., those with many attributes involved do not necessarily take more time.

3.1.1 Random Utility Theory

The crucial point here is that R.U.T. assumes that decisions are rational, to be more exact, it is the way an alternative is chosen over other ones. Thurstone modelled such a choice as early as in 1927 as a discriminal process of two objects at a time, based on the respective individual's subjective judgement of an attribute or trait of that object. He called this pairwise comparison law of comparative judgement. Importantly, it also be applied to make a choice from a large amount of alternatives, by comparing two objects at a time, one after another.

In R.U.T., every decision maker it thought to maximize utility by making a choice from a choice set, i. e., the range of alternatives at stake in a choice situation. S/he maximizes utility by choosing the alternative with the highest attractiveness, i. e., yielding the highest utility. Utility is constituted by a number of measurable characteristics which are attributes of the alternatives (Cascetta, 2009, p. 90). One of the advantages of R.U.T. is that it is compensatory, meaning that it allows for the compensation of negative attributes with positive ones or trading off one attribute against another (ibid.). This is also the case in many real-life situations.

The characteristics approach goes back to (Lancaster, 1966). His consumption theory postulates that goods are not the direct objects of utility but that it is their properties from which utility is derived. Utility maximization means that individuals choose the alternative with the properties or attributes that promise the highest utility. This very central assumption of R.U.T. is also captured in the utility function. It represents the utility that a specific product gives to a consumer or a group of consumers, which is equal to the sum of the utilities of the single attributes of personal relevance. Those attributes can e. g., be price, taste or color of a product.

As already stated, the utilities attached to each attribute are reflected in equation (1), the utility function:

$$U = \beta_0 + \beta_1 * \text{Attribute } 1 + \beta_2 * \text{Attribute } 2 + \beta_3 * \text{Attribute } 3 + \beta_4 * \text{Attribute } 4 + \text{Error term} \quad (1)$$

Based on this individual utility function, the decision maker performs operations according to a fixed decision rule to make a choice, i. e., s/he chooses one alternative from the alternative space. His or her goal is utility maximization (Manski, 1977).

Choice is consistent with R.U.T. if it reflects the choice probabilities that the random utility contains, so that the alternative with the highest choice probability is drawn (Louviere et al., 2000). However, term “random” in R.U.T. comes from the fact that the utility of a bundle of attributes that constitute a product varies across individuals as a random variable (Hofacker, 2007, p. 168). This random component is the second source of utility besides the product attributes in R.U.T. (Louviere et al., 2002). This means that R.U.T. acknowledges that a person may sometimes not choose what s/he actually prefers. Importantly, this is not due to changes in preferences or taste that are assumed to be stable, but due to random factors modeled in the error term of the utility function (Stigler & Becker, 1977).

When applying R.U.T. in practice, the researcher can choose from a variety of choice models. The data delivered by choice experiments is binary, it distinguishes between choice or non-choice of an alternative. Only when this data is merged with the data concerning attribute levels of each of the alternatives at stake, preferences and willingness to pay measures can be calculated.

Mathematically, the assumption that participants choose the product alternative providing them with the highest utility is modelled as in equation (2) where the probability of option *i* to be chosen is

$$P_{nsi} = Prob\left(U_{nsi} > U_{nsj}, \forall i \neq j\right) = Prob\left(V_{nsi} + \varepsilon_{nsi} > U_{nsj} + \varepsilon_{nsj}, \forall i \neq j\right) \qquad (2)$$

There is a variety of models to analyze choice data, e. g., multinomial logit and mixed logit. All of these models have specific assumptions. One assumption is that ε_{nsj} is identically and extreme value type 1 distributed, another one concerns independent normal distributions for the random coefficients (Hess & Hensher, 2010). If these assumptions are met, the probability that option *i* is chosen can be calculated in a multinomial logit model as in equation (3).

$$Prob(\, i \; is \; chosen) = \frac{exp(V_{nsi})}{\sum_{j=1}^{3} exp(V_{nsj})}, i = 1,2,3 \qquad (3)$$

Equation (3) is estimated using the simulated maximum likelihood method (Train, 2009). To calculate the willingness to pay, it is assumed that the price coefficient does not differ between consumers. How this is done using Stata's mixlogit and wtp commands to estimate the model will be explained in chapter 5.2.4. on the concrete example of the data from experiment I.

3.1.2. Approach on decision making in behavioral economics

Central to the notion of behavioral economics on decision making is the deviation from rationality meaning that all us of are less rational than standard economic theory assumes (Ariely, 2008, p. xviii). What Simon (1979) called bounded rationality challenged the notion that decision rules as utility maximization were appropriate to explain choice behavior. In fact, assuming that the decision rule was really carried out by the consumer implies that s/he solves the underlying equations of demand and cost functions (Simon, 1972). Deviating choice outcomes show that consumers neither do perform these equations nor have they perfect market knowledge, so classical theories modified these assumptions e. g., by introducing risk and uncertainty in the demand function, the cost function or both (ibid.). Other model modifications resulted in latent choice models. They add latent variables to discrete choice models, they incorporate attitudinal constructs in conventional economics models (Bolduc, 2008).

Still, this notion on decision making, although it accounts for altitudes and perceptions as latent variables (ibid.), is a different approach than behavioral scientists' explanation for deviations from rationality, so-called heuristics. Simon (1979) illustrates that at the example of a skilled chess player. A chess player does not consider all possible next moves but reduces the consideration to a subset by the use of heuristics. Heuristics "tend to guide the search into promising regions, so that solutions will generally be found after search of only a tiny part of the total space" (Simon, 1979). Heuristics enable humans to deal with complex situations, i. e., enable quicker decisions while reducing mental load. These very useful shortcuts to reduce complexity in everyday life are not always conscious to the decision maker. The crucial point is that as the use of heuristics produces irrational behavior in the same way repeatedly, the irrationality becomes predictably irrational. Sources of irrational behavior according are (Ariely, 2008, p. 7ff).:

- Relativity; humans framing choice alternatives not considering the full choice set but do so relative to the alternatives or those being present in the choice situation
- The anchoring effect; concerning price, this means an association of a product's value with a price that was paid before. Although prices might have changed over time, the

price of the first product of that kind bought determines its subjective value over a long period of time (ibid., p.27f).

- The concept “FREE!”; the fact that rational considerations of the upsides and downsides of products or services were shown to be complicated in a series of experiments when they were labelled as “for free” (ibid., p. 54) makes this concept by Ariely another source of irrational behavior

The same holds true for social norms (ibid., p. 45ff), being paid (ibid., p. 103ff) and emotions, especially sexual arousal (ibid., p. 119ff). Ariely also derives implications for social policy from his insights in human decision making (ibid., p. 68). He reasons that, e. g., the strong preference for products labelled as free could be used to dramatically increase the share of electric cars by lowering its registration costs to 0. In comparison to current lowered registration fees, the further reduction to zero registration costs would therefore have an over proportional effect on respective registration numbers.

In this dissertation, the preference for the color green, and an according negative reaction to red found in previous research (e. g., Thorndike et al., 2014) was used to set up two changes in the choice architecture in experiment II. First, an on-screen instant dynamic feedback on the amount of calories currently in the shopping basket used the positive and encouraging effect of the color green to communicate to participants that their order was fine. Only when a certain amount of calories was exceeded, the color red appeared to signal the contrary, i. e., to stop ordering more or even remove food items from the shopping basket. The design of the second change in choice architecture in experiment II was also based on the affirmative effect of the color green. It highlights a range of low calorie menu items to increase its choice rate.

Nudging, similar to Ariely’s upper approach to change human behavior is another, recently very popular attempt to exploit insights from behavioral economics to influence choice behavior. It also uses the knowledge about biases produced by the use of heuristics in human decision making to design nudges (Thaler & Sunstein, 2008) and is defined as purposeful changes in the choice context to influence behavior. These changes “guide and enable individuals to make choices almost automatically” (Lehner et al., 2015). The probably most famous example of heuristics or other types of mental shortcuts producing biases leading to irrational behavior (Tversky & Kahneman, 1974) which was used to design a nudging measure is the installation of miniature soccer goals inside the urinals at the airport in Amsterdam. It significantly reduced the need for cleaning by making many men voluntarily be more careful in a playful way when using the urinal, probably without most of them even realizing that they were being nudged when targeting at the soccer goal (Thaler & Sunstein, 2008, p. 12).

Accordingly, the big step that behavioral economics made was to use the knowledge about the systematic deviations of humans from rational choice by altering the choice context. A nudge is per definition “any aspect of the choice architecture that alters people’s behavior in a predictable way without forbidding any options or significantly changing their economic incentives. To count as a mere nudge, the intervention must be easy and cheap to avoid (Thaler & Sunstein, 2008, p. 8).

Another important point that needs to be emphasized here is that with nudging, “people’s choices are actively guided in their best interests but they remain at liberty to behave differently” (Marteau et al., 2011). However, there has also been criticism that nudging is paternalistic (Moens, 2015). This issue will be picked up again in chapter 7.

It is noteworthy that R. U. T. from classical economic theory and approaches on decision making from behavioral economics do not contradict each other. They are rather address two different agents in the human brain where one causes fast thinking while the other one causes slow thinking (Kahnemann, 2011, p. 25). Kahnemann calls these two agents system 1 and system 2. In some situations, the involuntarily actions from system 1 determine behavior and choice outcomes while in others the consciously controlled operations from system 2 do so. Kahnemann reasons that deviations from rationality come from characteristics of system 1 (ibid., p. 26). However, system 1 is essential to deal with the complexity of many situations and tasks. Animals are also thought to act on behalf of system 1, it is related to the capacity to perceive what is happening in the environment, identify subjects, steer attention and avoid losses. Practical examples are fleeing from spiders, identifying where a noise comes from but also habitually reacting when driving a car (ibid., p. 33f). All these intuitive reactions have been important for survival, especially in former times where half a second of decision time to climb a tree could determine if one was to become pray to tiger. Kahnemann reasons that system 1 was formed in evolution to constantly evaluate the problems an organism needs to consider and solve to survive (ibid., p. 118). System 2, by contrast, consciously analyzes situations to come to a decision and is used when making well-reflected decision as buying a house (ibid., p. 113). As it is of minor importance for this dissertation, it shall not be explained further.

3.1.3. Approach on decision making in this thesis

In the experiment I that essay I is based on, participants had to decide for their preferred setup of smart electricity meters. This experimental design fits the underlying research question which was to find the best setup concerning several functions of the smart electricity meter. Therefore, a choice experiment relating to classical economic theory, namely R.U.T (see chapter 3.1.1.) was performed. In the experiment II, that essays II and III are based on, participants faced a situation where they were being nudged to order less calories. This is why its experimental design clearly relates to insights from behavioral economics.

3.2. Research on consumer information

Before the following subchapters will outline how information is thought to influence consumer choices under the two paradigms on decision making introduced before, some general remarks on how to improve consumer information will be given.

3.2.1. Recommendations for good consumer information

The Federation of German Consumer Organizations (vzbv) published several remarks on how to improve consumer information. To reduce information overload, they recommend targeting well-defined consumer groups instead of the average consumer. Target groups should consider the everyday life of consumers and better exploit the possibilities information technology offers (Gillen et al., p. 8). Figure 4 shows a schematic representation of recommendations for effective consumer information.

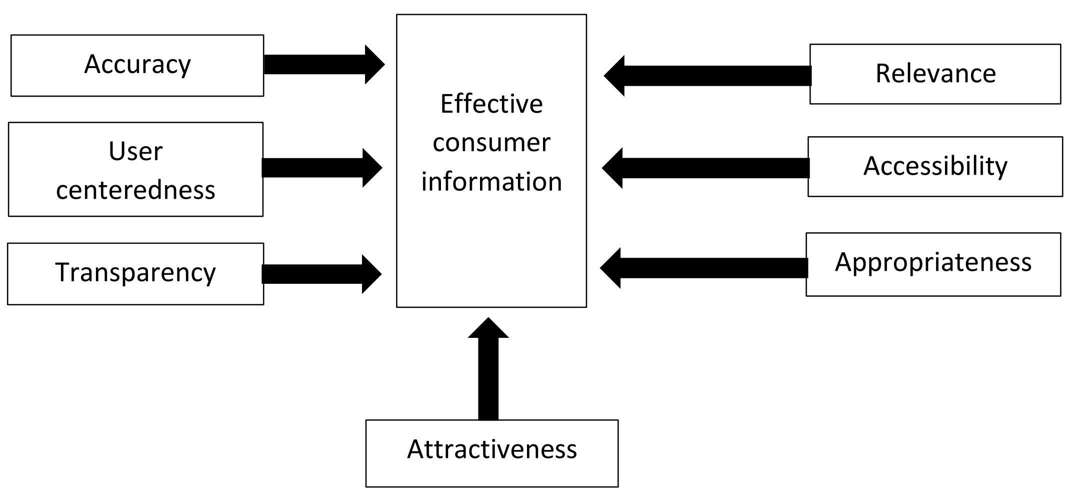


Figure 4: Recommendations for effective consumer information

Source: Gillen et al. (2012), p. 13

- Accuracy: Factual correctness, actuality, verifiability, reputable reduction in complexity, balance between completeness and understandability
- Relevance: Availability of necessary factual or situational information, reference to relevant supplementary information, facilitation of impact assessment, exemplification
- Accessibility: Physical perceptibility (font size, placement, volume, readability), low-threshold expense, barrier liberty, avoidance of linguistic misunderstandings
- Appropriateness: Nature and scope relating to the subject and the decision situation
- Attractiveness: Structure and presentation in line with common communication patterns (important things first, logical and chronological order, red thread, recognition value)
- Transparency: Recognizability, objectivity, competence of the sender, user focus
- User Centeredness: Determination of the target group, consideration of users with special needs (the elderly, children, emotionally affected). User test can be performed to enhance user satisfaction and effectiveness.

3.2.2. New types of consumer information

Consumer information types can be derived from several criteria: While there are search, experience & credence goods, it is possible to derive according information types:

- Search information allows quality evaluation before the purchase
- Experience information comes from experience gained in usage, consumption and further processing of products
- Expert information is information from persons and institutions with expertise about quality of goods that consumers cannot judge correctly (Kuhlmann, 1990, p. 332).

Also, the different phases of problem solving related to consumption decisions require different information: (1) problem recognition and goal determination, (2) evaluation of alternatives (3) purchase, (4) usage and consumption (ibid., p. 270). Another distinguishing criterion can be the intention of the producer or sender of the information, e. g., information vs. advertisement (see chapters 1.3 and 1.4).

A distinction that is of major interest and that this chapter will focus on is the one between "analog" and digital consumer information. Only digital consumer information can provide dynamic and personalized feedback, which can be described as a new type of consumer information (see also chapter 1.1.). Dynamic feedback is an instant response as soon as e. g., the amount of calories in the shopping basket changes. Personalized feedback is another possible application of consumer information on digital devices. An example is feedback taking into account personal characteristics like the body mass index of the user. Although this is not being used in the experiments of this thesis, this type of feedback has great potential Another possible data source for personalized feedback is the composition of the previous meals ordered so that a suggestion for a calorie reduced meal that better fits consumers' preferences could be made. Personalized feedback can enhance consumer acceptance as it increases, the fit of alternative products suggested by the system with consumer preferences.

Another consumer benefit of dynamic feedback on digital devices is easier and more structured accessibility to information. Essay I shows that consumers appreciate this at the example of a display showing electricity consumption patterns separated by time, rooms and devices. Dynamic feedback also enables new beneficial functions as electricity savings as shown in essay I.

As dynamic feedback on digital devices works with interlinked devices at the stage of the internet of things, data security becomes an issue. This is especially critical when an increasing amount of personal data is passed to retailers, suppliers or providers of services for the sake of receiving back dynamic feedback and other types of consumer information. Therefore, data security issues were explicitly incorporated in the design of the experiment essay I is based on. Radiation due to smart home devices is another sensitive issue related to the topic (Naus et al., 2014) that also was taken account for.

3.2.3. The impact of information on decision making in the context of R.U.T.

The following paragraphs will line out how information changes decisions under the paradigm of R.U.T. Full information means that consumers know all products on the market, i. e., all compositions of attribute expressions of these products. However, consumer markets are informationally imperfect (Maynes & Assum, 1982) so part of the product information is unknown to consumers which can lead to suboptimal decisions. These leave consumers with a suboptimal choice, which is not only undesirable for the individual consumer but also problematic for societies due to welfare loss (Milkman et al., 2008).

One possible impact of successful consumer information under the paradigm of R.U.T results in consumers spending less money on a good than they would have done without considering the information. Or they receive a product of higher quality for the same price. These direct effects of consumer information come from increased market transparency leading to enhanced market efficiency (Kuhlmann, 1990, p. 376). Consumers also can benefit from indirect effects of consumer information, being cheaper products or products of higher quality on the market due to more competition and marketing (ibid, p. 82).

There is a whole stream of economic literature examining if consumers take up and use information and act in a way the respective information suggested. Results are mixed. Calorie information was found to reduce calorie intake (Wisdom et al., 2010). Schooling on the topic of the relationship between health behavior and health-related behavior led to an increase in healthy behavior in terms of consumption of cigarettes, alcohol and exercise (Kenkel, 1991). Health-related information about food manipulated with means of nanotechnology was found to reduce the willingness to pay for such juice (Marette et al., 2009) which allows the conclusion on a behavioral impact of this kind of information in terms of a lower purchase rate of such products. However, information provision to risk groups to adjust their food consumption did not show the intended effect, neither short- not long-term in an experiment by Blanchemanche et al. (2010). More generally speaking, consumer information can have an effect on the consumer at several stages of the process of decision making. Every consumer is assumed to have an awareness- or knowledge-set consisting of only a subset of all products available on the market (universal set) in a product category (Shocker et al., 1991, p. 183). The consideration set is framed to evolve from the awareness set, accordingly. It is “purposefully constructed and can be viewed as consisting of those goal-satisfying alternatives salient or accessible on a particular occasion” (ibid.). Finally, the choice set is defined as the “final consideration set, i. e., the set of alternatives considered immediately prior to choice” (ibid.). Figure 5 lines out that consumer information can influence the composition of products in the awareness, consideration and choice set.

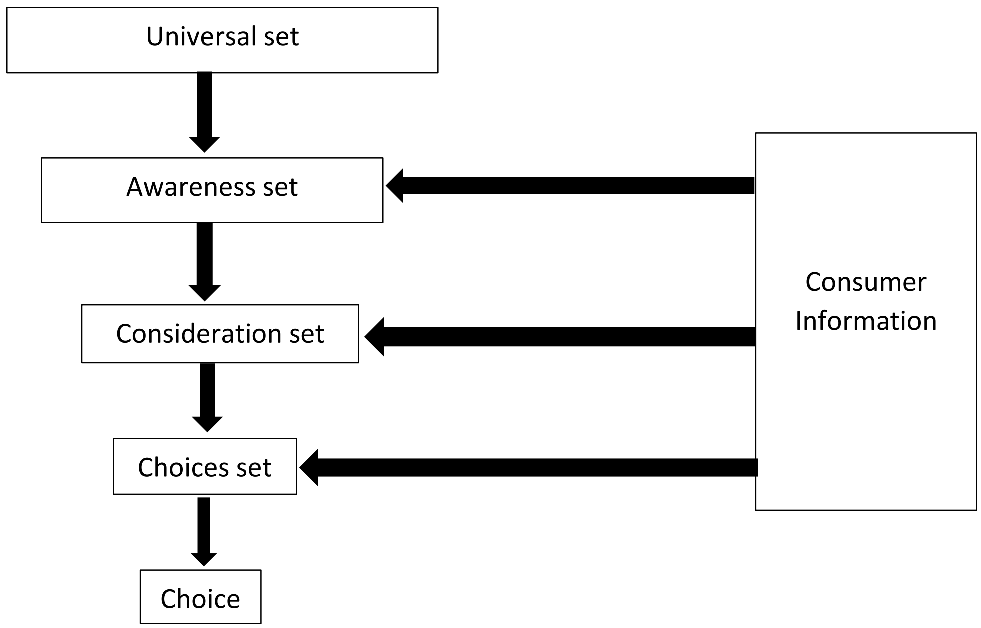


Figure 5: The role of consumer information in different stages of consumer choice

Source: Own illustration following Shocker et al. (1991)

Apart from making the consumer familiar with a new product on the market, consumer information can change the relative weight of attributes. If the information is relevant to the consumer, it can (1) change the composition of products in the respective set or (2) change its attribute values. This leads to a change in the utility function as new information made certain attributes less or more relevant. Final choice depends (1) on the composition of the final choice set on, which the previous sets also have an influence (see Figure 6) and (2) the attribute vectors according to which the choice is made according to the decision rule (see chapter 3.1.1.). In both cases, consumer information can have choice-changing influence.

3.2.4. The impact of information in behavioral economics

As already explained in chapter 3.1.2., behavioral economists do not doubt that certain choices are made after careful and systematic consideration of the alternatives at stake. However, even those careful and conscious decisions that are located in system 2 are thought to be influenced by system 1 which can produce biases as "its input never stops" (Kahnemann, 2011, p. 113). Behavioral economists aim to influence behavior via system 1 by changing the choice context so that choice outcomes are altered in the best interest of the person being nudged (Thaler & Sunstein, 2008). It is especially complex choice situations where nudging and other means of behavioral economics are fruitfully applied to improve consumer choices. Traditional consumer information provision can co-exist with the new approaches to influence consumers from behavioral economics when both are applied situationally. Figure 6 shows how consumer policy measures from both fields can be used to fulfill different tasks.

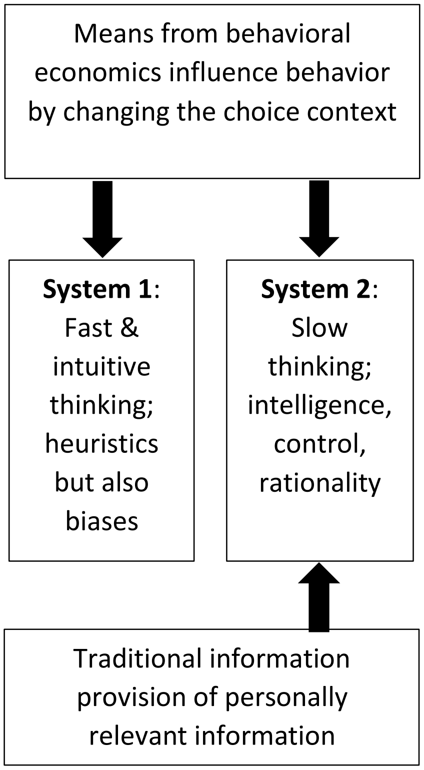


Figure 6: Consumer policy measures for system 1 and system 2

Source: Own illustration

4. *ESSAY I:* Consumers' willingness to pay for different setups of smart electricity meters [1]

Abstract

The legal situation in Germany has made the installation of communication-capable, i. e., smart electricity meters mandatory for an increasing number of private households. In this paper, we report the results of a discrete choice experiment (DCE) where consumers had to choose among different types of electricity meters. The DCE was combined with eye tracking measures recording the attention that consumers give to different meter characteristics. Results point to preferences and information needs of consumers with regard to smart electricity meters. We found that participants were willing to pay considerable price premiums for smart tariffs where electronic devices are automatically switched on/off at times of low/high electricity prices, for a display that shows consumption patterns over time and for single rooms and devices and for enhanced data protection. Our results suggest that smart meters for private households should have the above stated functionalities and avoid causing radiation because radiation resulted in negative WTP. Results of eye tracking support willingness to pay measures by attention measures for valued attributes and underline the importance of data protection measures.

Keywords: Smart meter, smart grid, willingness to pay, energy turnaround, energy policy

---

[1] The paper was coauthored by Bernhard Mohr and Jutta Roosen. Bernhard Mohr designed the study, conducted the survey, performed the analyses and wrote the paper. Jutta Roosen provided advice on study design, data analysis and the development of the paper as well as editorial input.

Submission status: Submitted to the *International Journal of Consumer Research*

4.1. Introduction

Private households contribute to about one fourth of the total amount of electricity consumed in Germany (Umweltbundesamt, 2017). Despite increasing efficiency of household electricity devices, this share as well as the total amount of electricity consumed by households has not changed considerably since 1990 (ibid.). To improve this situation, German legislation recently passed a law that makes it mandatory for an increasing number of households to install smart electricity meters from 2017 onwards (Bundesregierung, 2016). Private households exceeding an annual consumption of 10.000 kWh of electricity are obliged to install "intelligent measurement systems" (iMSys) from 2017 on. In 2020, this threshold will decrease to 6.000 kWh (ibid.). An average private household only consumed 3.650 kWh of electricity per yeaer in 2014 (Frondel et al., 2015) and the share of households expected to be affected by the obilgation to install iMsys lies only at 5% (Verbraucherzentrale Bundesverband, 2015). The term iMsys used in German law shares its definition with what previous literature called smart meter. It can briefly be described as "advanced meters that identify consumption in more detail than conventional meters and communicate via a network back to the utility for monitoring and billing purposes" (The Climate Group, 2008).

The German law for the digitalization of the energy turnaround (Bundesregierung, 2016) follows the EU directive 2009/72/EC concerning common rules for the internal market in electricity (European Union, 2009). It rules that the introduction of intelligent metering systems should be based on a cost benefit analysis (CBA) for the implementation of iMSys that is to be performed by all memberstates seperately (European Commission, 2013). As the CBA was not positive, a large scale roll out of smart electricity meters (at least 80 percent by 2020) is, unlike in other member states, not obligatory in Germany (European Commission, 2014).

Attempts to raise consumers' awareness of and involvement with electricity consumption by giving feedback showed mixed results in previous literature. Wallenborn et al. (2011) found that households save between 5 and 15 percent of their electricity when given immediate feedback on their consumption. Gans et al. (2013) even find a decrease of 11 to 17 percent due to feedback on residential electricity consumption. Social comparisons, e. g., communicating the consumption of a neighbor, also showed positive effects on the electricity bill (Allcott, 2011). However, this effect decayed over the months after participants were confronted with the reference point (ibid.). From previous literature we identified three benefits and two shortcomings of smart meters that are most relevant from a consumer perspective (Krishnamurti et al., 2012; Fang et al., 2012; Ida et al., 2014; Park et al., 2014). One function of smart meters that is beneficial for consumers is its ability to display the electricity consumption in more detail than a conventional meter so that the main drivers of electricity consumption in a household can be identified. In reaction, the user can, e. g., switch off appliances in stand-by, change settings or replace devices. Second, a smart meter makes it possible to benefit from reduced electricity prices in times of high net load. Such price discounts can be granted to electricity consumers depending on the load in the power grid. Actually, providers have trouble ensuring grid stability due to the volatility in electricity production by renewable energies. One solution to this problem is to adjust demand to supply by granting lower prices during times of low demand or high supply. This market-based approach may improve grid stability and reduce the amount of electricity produced. To what extent consumers are willing to change their daily routines to exploit the flexible tariff is one question that our study seeks to answer. A third consumer benefit of smart electricity meters is that counter reading can be processed from outside the house, so that no company staff needs to enter the house to read the meter. While offering more convenience in service provision by the electricity supplier, this – as well as the meter's connectedness to the grid – raises concerns about data protection issues. Other publications also found that trust in the protection of personal smart meter data is an issue (Gerpott & Paukert; 2013, Barringer, 2011). In addition, grid connection is assured by a radiation signal that Barringer (2011) has shown to be perceived as a health threat by some consumers. In investigating willingness to pay (WTP) for different functions of smart meters, we follow Sovacool (2014) who criticizes that fact that social science related disciplines and especially human choice are dramatically underrepresented in energy studies research. To not confuse participants with a too complex setup in our choice experiment and to make choices relevant to all participants, we did not take into account benefits and shortcomings that relate to electric vehicles and photovoltaic panels connected to a smart meter proposed by Ida et al. (2014).

In order to understand the role of the different characteristics of smart meters, their benefits and associated risks in consumers' decision to adopt the technology, we conduct a study including a DCE for meter selection. Based on the results we identify consumer preferences and WTP for different functionalities. There is only a small amount of literature that elicited WTP for smart electricity meters. Ida et al. (2014) did so for Japanese consumers and found positive WTP for the features private home screen display, energy saving advice, and off-peak discount. Kaufmann et al. (2013) performed a choice-based conjoint study focused on the Swiss market and identified four customer segments all of which had positive WTP for different functionalities of smart meters. Those were remote meter reading with accurate monthly billing, real-time consumption feedback, programming and steering services and home security and surveillance services. Gerpott & Paukert (2013) focused on factors impacting WTP of German consumers. They found that trust in the protection of personal smart meter data and the intention to change one's electricity consumption behaviors after smart meter deployment most strongly related to WTP for smart meters.

In addition to the DCE, we measured consumers' socio-demographics and recorded participants' eye-movements with an eye tracker while they made their choices on the screen. We combine this data with the WTP measures to better understand the role of the different attributes and levels. We contribute to the discussion accompanying the introduction of smart meters in German private households by designing a DCE, where basic functions of smart meters that are realistic to enter the German market soon are tested.

The remainder of the paper is as follows. The next section presents data and methods. Then, we present the results of data analysis. Subsequently, the last section discusses the results of the study and concludes.

4.2. Methods

5.2.1. Sample

Eighty subjects from a midsize university town in Southern Germany participated in our lab experiment in November 2014. The experiment took place on campus in a room that was exclusively dedicated to the experiment. The small number of participants is due to the long duration of the experiment of approximately 90 minutes and the individual eye tracking measures. Table 1 presents means and standard deviations of variables describing the sample.

Table 1: Sample demographics and other characteristics, given as mean values with standard deviations and/ or frequency in percent

	Mean (std. dev.)	Frequency (%)
Gender		
Male		51
Female		49
Age	38.10 (15.72)	
Household size	2.83 (1.69)	
Presence of child/ children under the age of 18		
yes		19
no		81
Education (completed level)		
No completed education yet		15.00
Vocational training in the dual system		18.8
Professional school degree		15.00
(Professional) academy degree		2.50
(Technical) college degree		12.50
University degree		33.8
PhD		2.50
Net Monthly Household Income		
Below 1 300 €		30
1 300 - 2 600 €		24
2 600 – 3 600 €		25
3 600 – 5 000 €		15
More than 5 000 €		5
Psychographic Variables		
Ecological worldview (1-5)	3.69 (.56)	
Time preference (1-20)	11.86 (5.51)	
Risk aversion (1-10)	5.28 (2.13)	
Altruism (1-5)	3.78 (.72)	
Novelty seeking (1-7)	3.55 (1.13)	
Monthly household electricity bill	81.18 (64.96)	
Already heard of smart meters		
Yes		37
No		63
Owner of smart meter at home		
Yes		5
No		66
Don't know		29

Participants were between 16 and 74 years old, mean age was 38.1 years (SD=15.7). 39 of 80 participants were women. Average household size was 2.83, of which 19% had children under 18. The average household electricity bill amounted to 81.18 Euros per month.

Our sample was better educated than the overall population with 49 percent holding a Bachelor's, Master's or equivalent degree. Average household income was also considerably high with 45% of households exceeding a net monthly household income of 2 600 Euros while 20% even exceed 3 600 Euros. Only 31% stayed below the threshold of 1 300 Euros.

We also measured psychographic variables. We used the NEP scale by Dunlap et al., (2000) asking for ecological worldview. Time preference was measured by the method proposed by Dohmen et al. (2007) and risk aversion on a 10-point Likert scale. In addition, we measured altruism using the respective items of the G-SOEP as provided in Richter et al. (1993). Novelty seeking was measured by an own German translation of the consumer innovativeness scale (Manning et al. in Bearden et al.,1993).

Participants' average score of the ecological worldview scale was 3.7 which was higher than what was measured in other experiments (e. g., Denis & Pereira, 2014). This indicates that 97.5 percent of our sample share a pro-ecological worldview (Lawton, 2016). The time preference measure shows an average score of 11.9, meaning that 49 percent of participants are rather patient. We also asked for risk-aversion on a 10-point-Likert scale with an average score of 5.3. Hence, 46 percent turned out to be rather risk-averse while 54 percent were rather risk seeking. Furthermore, we found that the majority of participants can be classified as altruistic (92.5 percent with a score larger than 2.5) with a mean score of 3.78. There is no clear tendency in terms of novelty seeking with a mean score of 2.55. 46.25 percent are rather novelty seeking. Finally, we asked if participants ever heard of smart electricity meters before the experiment which was the case for only 5 percent of households in our sample.

5.2.2. Choice experiment

The experiment lasted about 90 minutes and, after signing informed consent, participants were asked to fill in a pre-experiment pen & paper questionnaire that asked for household size, household income, education, gender and other variables such as altruism and novelty seeking. We used those variables to predict the missing values for monthly electricity bill in a regression model.

The first questionnaire was followed by the choice experiment which started with an information page on smart meters. The text was meant to inform all participants about the different functionalities that entered our choice experiment as attributes and levels of the smart meters. The English translation of this text is provided in Appendix 1. All participants could take as much time as needed to read the text.

The information was directly followed by the choice experiment. Participants were seated in front of a computer screen and calibration for the eye tracking procedure was performed. The choice experiment on the screen was programmed with the online survey tool Unipark/ Questback. We instructed participants to make a choice between three discrete alternatives, i. e., two setups of smart meters and a status-quo option, in 24 choice sets. A post-experiment questionnaire asked for time preference using the method proposed by Dohmen et al. (2007).

Table 2 shows the attributes and corresponding attribute levels that it is based on.

Table 2: Smart meter's attributes and corresponding attribute levels for the choice experiment

Attribute	Attribute-level 0	Attribute-level 1	Attribute-level 2	Attribute-level 3
Consumption display	Current consumption (common way of display)	Consumption by time (months/ days/ hours)	Consumption by time and separate rooms	Consumption by time, separate rooms & devices
Smart tariff	No smart tariff (flat tariff)	Traffic light signal on meter (indicates normal vs. reduced tariff)	With prior user consent, selected devices automatically turn on if reduced tariff available	
Data protection	Data Protection according to legal standard	Technical solution for increased data protection against threats from outside		
Radiation	No radiation (only in alternative 3)	Data transfer via weak radiation signal every 15 minutes	Technical solution lowers radiation produced by the smart meter	
Price	No change in monthly electricity bill	5% lower monthly electricity bill	10% lower monthly electricity bill	5% higher monthly electricity bill

The attribute "complexity of consumption display" has three attribute levels. In the base level 0, one can only read the current height of electricity consumption as on most contemporarily common electricity meters. Level 1 is defined as displaying consumption patterns on a screen over time; level 2 adds a distinction by separate rooms and levels, 3 by separate devices.

The 0-level of the attribute smart tariff is defined as unified tariff because there is no smart tariff available. Level 1 is labelled as "traffic light label on meter indicates current tariff (normal or reduced)" while level 2 was "With prior user consent, selected devices automatically turn on if reduced tariff available". In the introductory text that participants could read right before the start of the experiment (Appendix 1), this procedure was explained in more detail at the example of a washing machine. Participants were told that the washing machine would need to be switched to the respective mode so that in case of tariff change, washing would begin. This example illustrates why we call this attribute smart tariff: It is “smarter” than the common net load flexible tariff of which level 2 is the” smartest” one.

The attribute “data protection” has two levels: Data protection meeting legal standards (level 0) and a technical solution for enhanced protection against threats from outside the home (level 1). The respective attribute levels of the attribute radiation are “data transfer via a weak radiation signal every 15 minutes” (level 1) and “a technical solution to reduce radiation produced by the smart meter” (level 2). The attribute price has four levels: No change (level 0), 5% decrease in monthly electricity bill (level 1), a respective 10% decrease (level 2) and a respective 5% increase (level 3). An advantage of communicating price in relation to the current amount of the electricity bill and not in absolute numbers is that it accounts for the fact that monthly electricity bills differ considerably among households. Absolute numbers would have caused different utilities for different respondents as consumers tend to judge price discounts or premiums in relation to the initial price (Janiszewski et al. (2004)).

Based on these attributes and levels, a fractional factorial optimal on differences design was developed for the choice experiment using the software NGene. The design yielded 24 choice sets in which participants had to choose between two versions of a smart meter and a status-quo option that was labelled as “I rather choose a common meter”.

5.2.3. Eye tracking information

During the choice experiment, eye-movements were recorded using a Tobii 60XL eye tracker. According to the eye-mind hypothesis, knowing what a person looks at allows inferences on where this person's attention is being directed (Poole & Ball, 2006). In other words recordings of eye-movement provide a "dynamic trace of where a person's attention is being directed in relation to a visual display" (Ghaoui, 2006, p. 212).

Accordingly, the use of eye tracking accompanying the choice experiment aims to answer the question which attributes participants pay most attention to. The combination of the two makes it possible to make a stronger statement on features of smart meters that are relevant for consumers than when only considering one of the two methods. In the software Tobii Studio that we used for data analysis, we defined areas of interest (AOI) in the form of rectangles covering certain parts of the screen. In our case, there were five AOIs, one for each attribute. We used the standard settings concerning the threshold for fixation counts. Recordings were excluded from the analysis when less than 70% of eye movements were recorded by the device. This was the case for 12 of 80 participants. The choice experiment was followed by another questionnaire on three electricity-related internet sites that participants had to choose and explore online. Finally, an exit questionnaire including the time preference scale and some debriefing questions and the receipt of 30 Euros concluded the experiment.

5.2.4. Estimation

Following Hensher et al. (2015), choices by participants are modeled based on the random utility model. Let U_{nsi} denote the utility that individual *n* obtains from choosing option *i* in choice set *s*. This utility is assumed to be partitioned in an observable, deterministic part of utility V_{nsi} and an unobservable, random part ε_{nsi}. The deterministic component of utility depends on the level of attributes and the corresponding parameters, representing the marginal utility of each attribute and level as shown:

$$\begin{aligned} V_{nsi} = {} & \beta_1\, display\ time_{\ nsi} + \beta_2\, display\ room_{\ nsi} + \beta_3\, display\ device_{\ nsi} + \\ & \beta_4 Smart\ tariff\ TL_{nsi} + \beta_5\, Smart\ tariff\ remote_{nsi} + \beta_5\, Data\ protection_{nsi} + \\ & \beta_6\, Radition_{nsi} + \beta_7\, Reduced\ Radiation_{nsi} + \beta_8\, price_{nsi} \end{aligned} \qquad (1)$$

According to the theory of comparative judgement that was introduced by Thurstone in 1927, it is assumed that participants choose the product alternative that provides them with the highest utility. Thus, the probability of option *i* results as

$$P_{nsi} = Prob\big(U_{nsi} > U_{nsj}, \forall i \neq j\big) = Prob\big(V_{nsi} + \varepsilon_{nsi} > U_{nsj} + \varepsilon_{nsj}, \forall i \neq j\big) \qquad (2)$$

Assuming that the errors are extreme value distributed, the probability that option *i* is chosen results in a multinomial logit model as

$$Prob(\ i\ is\ chosen) = \frac{exp(V_{nsi})}{\sum_{j=1}^{3} exp\big(V_{nsj}\big)}, i = 1,2,3 \qquad (3)$$

We analyzed the data by calculating a multinomial logit model where the alternative chosen is the dependent variable. Data on attribute levels were dummy coded but price enters the estimation as metric variable. In the status-quo option, all attribute levels were set to zero. The estimation was done in Stata.

By systematic variation of the product attributes, i. e., attribute levels that are combined into choice sets, we infer on WTP for the respective attribute levels. To be able to obtain monetary WTP measures, we multiplied participants' monthly electricity bill with the respective price level (-10%, -5%, no change or +5%) before the price variable entered the logit model. For missing values in the variable electricity bill, we predicted the monthly electricity bill in a regression using household size, household income, education, gender, altruism and novelty seeking. Missing values in this variable were replaced for 39 percent of the observations. The R^2 of the regression was 0.386.

4.3. Results

Table 3 shows the results of our analysis.

Table 3: Multinomial logit coefficient estimates, WTP and fixation duration by attribute

Attribute & attribute-levels	**Coefficient**	**WTP in €**	**Fixation duration in seconds**
Price	-0.245***	---	40.4
Consumption display			84.2
Level 0: Current consumption (common display)	---	---	
Level 1: Consumption display by time	0.599***	2.44	
Level 2: Consumption display by time & rooms	0.392***	1.60	
Level 3: Consumption display by time, rooms & devices	0.626***	2.55	
Smart tariff			79.4
Level 0: no smart tariff (flat tariff)	---	---	
Level 1: Traffic light signals availability of reduced price	0.877***	3.57	
Level 2: Automatic switch-on if reduced tariff available	0.913***	3.72	
Data protection of content sent by or saved on meter			98.3
Level 0: Protection according to legal standards	---	---	
Level 1: Technical solution for enhanced protection	0.473***	1.93	
Radiation produced by meter			60.0
Level 0: No radiation	---	---	
Level 1: Weak radiation signal	-0.716***	-2.92	
Level 2: Technical solution to reduce radiation	-0.435***	-1.77	

***, **, * means significance at 0.01, 0.05, and 0.10, respectively

The first column of Table 3 shows the estimated coefficients of the multinomial logit model. All coefficients have the expected sign and are significant at the 1 percent level. The WTP values are derived by dividing the coefficient of the respective attribute level by the price coefficient. As already pointed out, the WTP measures at hand can be interpreted as monthly (de)charge in Euro and Cents on the electricity bill as their calculation is based on participants' monthly electricity bill. Confidence intervals were obtained in Stata using the wtp command. All coefficients are significant at the (.05) level.

Results demonstrate that the two levels of the attribute smart tariff elicit the highest WTP compared to all other attributes: The function of automatic switch on (3.72 €) even exceeds the traffic light attribute (3.57 €). This result demonstrates that consumers are highly willing to participate in the smart grid, and that they prefer the automated version. This also means that they are willing to give up some autonomy on when to do, e. g., their laundry and despite possible constraints concerning data protection and radiation.

We found the third highest WTP for the most sophisticated possibility to track electricity usage in more detail than on a current meter, namely by time, rooms and devices (2.55 €). Interestingly, within this attribute, participants were willing to pay more for the simplest display-setup that only shows consumption over time (2.44 €) than for the one differentiating by time and rooms (1.60 €). According to WTP-measures, participants found the attributes of data protection and radiation and the respective attribute levels least attractive. While a technical solution for increased data protection was valued with 1.93 €, radiation was the only attribute that elicited negative WTPs of -2.92 €. We described the radiation as a weak radio signal every 15 minutes to read the meter from outside the house or due to its connection to the wireless internet of the home. The attribute level technical solution to reduce radiation also elicited a negative WTP of -1.77 €. We interpret this result as participants having a strong aversion against the radiation signal while there is a less strong aversion for a meter with reduced radiation. This result calls for a meter that does not produce any radiation and can also be interpreted as a distrust against technical measures to reduce it.

The measurement of fixation duration by attributes via eye tracking confirm the WTP measures we obtained for most attributes. Relatively much attention (84.2 seconds, rank 2) was given to consumption display, closely followed by smart tariff (79.4 seconds, rank 3). Those two attributes also elicited highest WTP. Interestingly, fixation duration on the attribute of data protection was highest of all attributes (98.3 seconds, rank 1) despite low WTP. This result emphasizes the importance of the issue of data protection as participants paid more attention to it than to any other attribute. This, together with its low WTP, shows that consumers are very critical about the topic of data protection while the technical solution for enhanced protection was not convincing. Accordingly, the fact that lowest fixation duration (40.4 seconds, rank 5) was given to the price attribute can be interpreted as consumers considering it as relatively unimportant. Second lowest attention was given to radiation (60.0 seconds, rank 4). Connecting this result to its outstanding negative WTP measure implies that participants found the drastic decision against any kind of radiation relatively easy, which underlines the seriousness of the issue.

4.4. Discussion

It is worthy of discussion that the highest WTP was elicited by the attribute automatic switch-on. We interpret this as a willingness to change daily routines, e. g., by switching times of doing the laundry to times when electricity is cheap. This is a positive result for legislators who wonder if the consumer can be a part of the German energy turnaround in the future. However, electricity providers have to make an effort to bring net load flexible tariffs on the German market for private households soon so that the smart grid concept can work for a larger amount of users as currently, those tariffs are only available for companies.

The negative WTP for radiation produced by the smart meter is interesting in two ways. Considering the fact that most households have wireless internet as well as wireless and mobile phones, a weak radiation signal every 15 minutes, as we framed the smart meter radiation in our experiment, seems not very problematic from an objective point of view. However, while it leads to clear benefits for the user, namely making it obsolete that staff of the providing electricity company comes to the house and reads the meter as well as accurate monthly billing, radiation may raise fears concerning health issues and data security. This skepticism we found is somehow problematic for the acceptance of smart meters on the side of the consumer and is a challenge for marketers and legislators as current smart appliances do produce radiation due to their required connectedness to a wireless internet router.

Our WTP data cannot give a definite assessment on the motive for the high WTP for the feature automatic switch-on. It remains unclear if participants intend to save money by using the reduced tariff or if they are rather willing to support the energy turnaround in Germany for environmental consciousness reasons. We can shed more light on this question if we turn to our eye tracking results. The comparatively low fixation duration for the price attribute can be interpreted in a way that saving money is not the prior motive. Considering the fact that our sample is relatively wealthy and well-educated, further research needs to be done to find out if our findings also apply for the whole population, especially as other authors, e. g., Ida et al. (2014), found high price sensitivity in their sample.

Further analysis shows that the highest fixation durations generally fall on the attributes that also eliciting highest WTPs, namely consumption display and smart tariff. The attribute radiation gained comparatively little attention while it elicited negative WTP. The attribute data protection stands out in this respect: We measured the highest fixation duration on this attribute although its WTP was rather low. We interpret this as data protection being of great relevance to consumers. However, the consumer expects data protection in electricity meters and is not willing to pay a large premium for it. This is supported by previous literature that pointed out the importance of data protection issues in smart meters to consumers (Cavoukian et al., 2010). An alternative explanation for the high fixation duration on the attribute data protection is that the wording of its attribute levels may have been too vague as we only let participants choose between 'legal standards being met' and 'enhanced protection'. Having to interpret out the specific concepts standing behind these statements may also have increased fixation duration.

4.5. Conclusion

In this paper, we report WTP for smart electricity meters and combine this measure with eye tracking. By doing so, we intended to recommend preferred (combination of) functions/ setups of smart electricity meters. We found that participants were willing to pay considerable price premiums concerning the fact that their average monthly electricity bill was 81.18 Euros: 3.72 Euros for the function of automatic switch-on of pre-selected household devices in times of high net load, 2.55 Euros for a display that shows consumption patterns over time and for single rooms/ devices and 1.93 Euros for enhanced data protection. These price premiums add up to 8.20 Euros which is more than 10% of the average monthly electricity bill. Besides recommending the above described functional setups for smart electricity meters, we recommend to avoid causing radiation as it elicited negative WTP of -2.92 Euros for a weak radiation signal that can be diminished to -1.77 Euros by a technical solution to reduce radiation. Data protection issues should also be carefully considered.

5. *ESSAY II:* The influence of sex and self-control on the effectiveness of nudges to lower energy intake among young adults [2]

Abstract

We introduce modifications on a fast food ordering screen to test the effectiveness of different nudges including an order assistant, traffic light labeling and highlighting choices. These modifications were designed with the aim to reduce the amount of energy in terms of calories ordered by young adults. Our results show that the order assistant is the only intervention that leads to significantly fewer calories in the fast food order. The effect is due to women ordering fewer high-calorie dishes. Men, by contrast, are unresponsive to changes in the choice context regarding calories ordered. Results also indicate that the level of self-control moderates the impact of the feature highlighting choices so that higher levels of self-control lead to lower calorie intake for both sexes.

Keywords: Fast food, energy intake, nudging, self-control, sex

---

[2] The paper was coauthored by Bernhard Mohr, Irina Dolgopolova and Jutta Roosen. Bernhard Mohr designed the study, conducted the survey, performed the analyses and wrote the paper. Jutta Roosen provided advice on study design, data analysis and the development of the paper as well as editorial input. Irina Dolgopolova advised on data analysis, paper development and editing.

Submission status: Resubmitted to *Appetite*

5.1. Introduction

Increasing obesity rates in many countries of the world (WHO, 2017)[3] called for the development of measures to improve the quality of dietary intake among different groups of the population, for example, by reducing energy intake. In the literature, two major pathways of influencing consumers' energy intake emerged: Providing information and nudging (Downs et al., 2009). In this context, providing calorie information, and thus appealing to the rational consumer, in an attempt to reduce energy intake did not always result in the intended outcome (Drichoutis et al., 2009; James et al., 2015; Kiszko et al., 2014). Two systematic literature reviews about the impact of calorie menu labeling on consumer behavior, which analyze the results of 53 and 19 studies, respectively, conclude that it remains in general unclear if calorie labeling decreases energy intake (Bleich et al., 2017; Long et al., 2015). Against this background of calorie information not being an effective measure to decrease energy intake, an alternative method – nudging (Baron, 2010) – was proposed by behavioral economists. A nudge is defined as "any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives. To count as a mere nudge, the intervention must be easy and cheap to avoid" (Thaler & Sunstein, 2008, p. 6). Nudging practice relates to the paradigm of behavioral economics integrating a psychological perspective on choice behavior into the traditional economic approach. Central to its understanding is the systematic use of knowledge about the heuristics that humans use when making many of their decisions. Heuristics are a way of quick decision making under incomplete information or "rules of thumb" (Kahneman & Frederick, 2005). In contrast to consumer information, a nudge can alter consumer behavior without information being consciously taken into account in a choice situation. In the

[3] http://gamapserver.who.int/gho/interactive_charts/ncd/risk_factors/overweight/atlas.html, last accessed February 20, 2019.

context of away-from-home food settings, various nudges have been studied including labeling schemes, changes in portion sizes, menu designs, and food accessibility (Cohen & Babey, 2012). Results of nudging interventions have in general been demonstrated to improve dietary choices (Arno & Thomas, 2016; Bucher et al., 2016; Wilson et al., 2016). Approaching the consumer as a rational decision maker has a longer tradition in consumer research than looking at the consumer as a decision maker using heuristics. Thus, a considerable amount of research has been conducted on the effectiveness of providing information while taking into account heterogeneity among consumers. For example, significant differences between men and women were reported with regard to the frequency of and motivation for fast food consumption (Morse & Driskell, 2009). Moreover, previous research demonstrated significant differences between men and women in their reaction to the provision of calorie information. Women were more likely to use calorie information (Chen et al., 2015) and to choose lower calorie meals than men when information was provided (Gerend, 2009). However, heterogeneity with regard to sex in response to nudging interventions remains an understudied topic.

Furthermore, psychological factors involved in the decision-making processes, which have been considered important in research about the influence of information on energy content, are yet missing from research about the effectiveness of nudging. The effectiveness of information provision has been demonstrated to depend on the level of self-control (Rising & Bol, 2017). It was found that the presence of calorie labeling increases the likelihood of ordering food options with fewer calories only for individuals with higher levels of self-control. It is yet to be determined if psychological characteristics of consumers such as self-control play an important role in a decision-making process guided by heuristics.

Consequently, this paper aims to add insights into the influence of consumer characteristics such as sex and the level of self-control on the effectiveness of nudging interventions aiming to reduce energy intake. We approach this challenge by modifying the ordering screen of a popular fast food restaurant chain. To improve nutritional outcomes of the ordering process, i. e., to lower the amount of calories ordered, three experimental features that use elements of nudging are introduced on the ordering screen, separately and in combination with each other.

First, we deliver indirect information on the amount of calories ordered by facial expressions of an order assistant. The facial expressions are supported by text. Facial expressions demonstrating social approval or disapproval are also referred to as "injunctive messages" and have been tested as nudges in the context of energy conservation (Schultz et al., 2007) and food consumption (Vasiljevic et al., 2015). Second, we provide participants with numeric information on the amount of calories they have in their shopping basket supported by traffic light labeling. Traffic light labeling can be considered nudging as it triggers simplified decision-making processes (Roberto & Khandpur, 2014; Scrinis & Parker, 2016). However, the effectiveness of traffic light labels remains unclear. For example, Seward et al. (2016) found no significant effect of traffic light label interventions on calorie intake in university cafeterias. No change in calorie intake as a response to the presence of traffic light labeling was also reported by Ebel et al. (2013). Third, present-biased preferences are exploited by highlighting low calorie items using a different background color, a green bar. Present-biased preferences normally lead to unhealthy choices because individuals prefer enjoying a meal immediately over avoiding weight gain in the future (Downs et al., 2009). By using color background schemes, we decrease the immediate cost of making a healthy choice by highlighting healthy dishes using a different color background.

Among different age groups, young adulthood is characterized by a high risk of becoming obese (Allman-Farinelli, 2015; Zheng et al., 2017). In developed countries reasons for obesity among young adults include the increased consumption of food away from home, including fast food (Larson et al., 2011). Furthermore, studies among young adults report a direct link between an increase in the body mass index (BMI) and the consumption of fast food (Rosenheck, 2008). However, obesity among young adults remains an understudied topic (Zheng et al., 2017).

Against this background, we investigate young adults' food choices on a tablet screen imitating the order terminal in a well-known fast food restaurant. A tablet screen was chosen as an order platform not only because it is increasingly found in online shopping, but also in fast food environments in form of order terminals. Furthermore, digital communication devices can help to provide personalized information and instant dynamic feedback in the ordering process, thereby making information more relevant for consumers and helping them to engage in the ordering process.

To sum up, this paper responds to the following gaps identified in the literature. First, it addresses the effectiveness of different nudging measures in modifying food choice outcomes among young adults. Second, it provides additional evidence on the influence of sex and self-control on decision-making of young adults regarding fast food choices.

The structure of the paper is as follows. The next section presents data and methods where subjects and procedures are described as is the design of the ordering screen that was specifically developed for this study. We present and discuss the results in sections 3 and 4 and conclude in section 5.

5.2. Data and methods

5.2.1. Subjects and procedure

The experiment was approved by the Ethics Board of Technical University of Munich and took place in September and October 2016. Participants were undergraduate students of the same university who were intercepted at a central university building. Students were eligible to participate in the survey if they consumed fast food at least once per month. Overall, we obtained data from 401 subjects. Around 50% of the sample were women; the average age was 19.54 years. Respondents consumed fast food on average five times a month.

The experiment lasted for approximately 30 minutes. After filling in a consent form and answering a pre-experiment questionnaire, respondents received a XL 12.2-inch tablet computer where a hypothetical fast food order had to be made. In the beginning of the experiment, subjects saw a first interaction screen that allowed them to enter their calorie goal for the order. The first screen is shown in Appendix 3. A default of 700 calories automatically appeared and could be changed by the participant. While the German society of nutrition (DGE) recommends 700 calories per meal when assuming three meals per day, nutritional needs can differ considerably between individuals, e. g., due to previous physical activity or body weight. We accounted for these differences by giving the opportunity to change the calorie goal to any number before the actual order started. After participants confirmed their personal calorie goal, the ordering screen displayed in Figure 7 appeared on the screen.

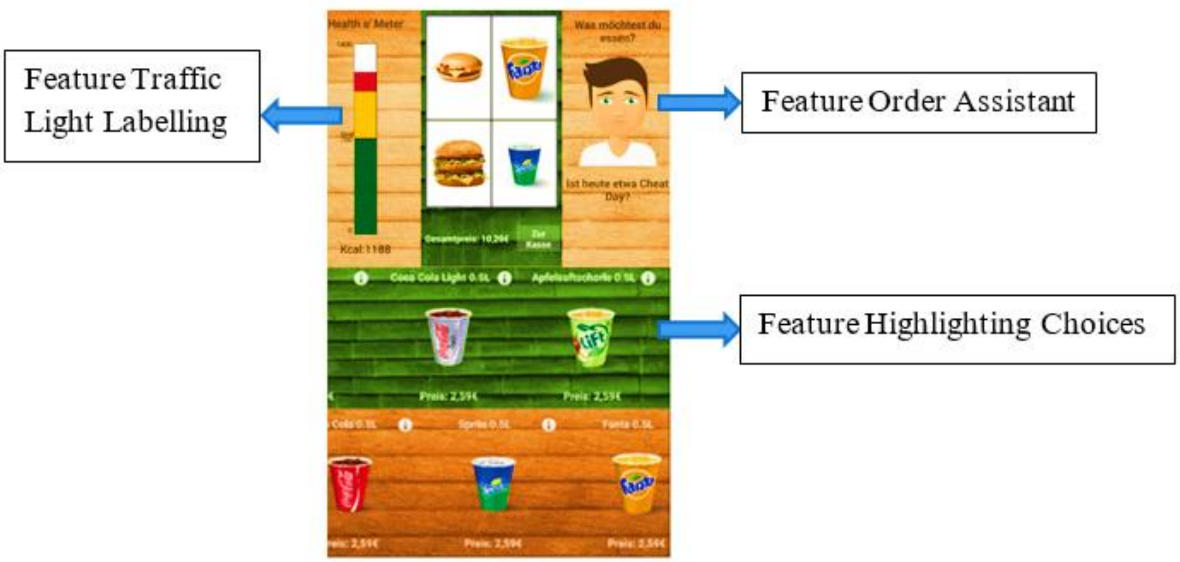


Figure 7: Ordering screen with all features switched on

Participants could form their order by choosing from twenty dishes of which ten were presented in the upper bar and ten in the lower bar by swiping to the left or right and adding dishes to the shopping basket by touch. The possibility to swipe was indicated to participants by a hand with two arrows that appeared when they saw the screen for the first time. Available dishes along with the respective nutrition information are presented in Appendix 2. We selected the twenty dishes so that it is possible to choose a complete meal, including a main dish, a side dish and a drink, from each bar. The upper bar presented lower-calorie dishes with an average calorie content per dish of 186 kcal. The lower bar contained higher-calorie dishes with an average of 378 kcal per dish. There was a difference in average price which we aimed to keep as small as possible to have no price effect (average price upper bar: 2.86 Euros; lower bar: 3.20 Euros). After the food order was completed, the experiment closed with an exit questionnaire. Participants received 10 Euros in cash to compensate for their time.

5.2.2. Experimental features of the ordering screen

5.2.2.1. Order assistant

The assistant (top right in Figure 7) is an animated human face that changes its facial expression depending on the current amount of calories in the shopping basket. Right below his picture, a message appears that fits the respective facial expression and depends on the calories that the shopping basket currently contains. The assistant has five different facial expressions and respective verbal messages. We describe those combinations in Table 4.

Table 4: Order assistant's reactions to the amount of calories in the order (an example with default option of 700 kcal)

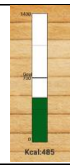
Calories ordered	0	1 – 700[a]	701 – 1050[b]	1051 – 1400[c]	> 1400[d]
Order assistant's facial expression	Neutral 	Happy 	Surprised 	Critical 	Shocked 
Order assistant's verbal message	Please touch on a product to choose it!	Great choice!	Oh! You are above your calorie goal.	Is today your cheat day?	Are you sure?

[a] the upper limit changes depending on the amount of calories specified by a participant as a calorie goal.
[b] the lower limit is calculated as the calorie goal specified by a participant +1, the upper limit is calculated as calorie goal × 1.5.
[c] the lower limit is calculated as (calorie goal × 1.5) + 1, the upper limit is calculated as calorie goal × 2.
[d] is calculated as calorie goal × 2.

5.2.2.2. Traffic light labelling

The amount of calories that the current order contains is displayed in the upper left part of Figure 2 along with a graphical representation similar to a thermometer changing color systematically from green to red. Table 5 demonstrates changes in colors depending on the calorie content of the current order.

Table 5: Traffic light labeling changes depending on the amount of calories in the order (an example with default option of 700 kcal)

Calories ordered	0	1 – 700	701 – 1050*	1051 – 1400*	> 1400*
Colors in traffic light labeling	White/blank	Green	Green + yellow	Green + yellow + red	Green + yellow + red
Example traffic light labeling					

* Upper and lower limits calculated as in Table 4

5.2.2.3. Highlighting choices

The lower part of Figure 7 presents two groups of possible product choices in bars that can be swiped to left and to right. When the highlighting choices feature is switched on, the upper bar with products is colored green. Otherwise, when the feature is absent, both bars appear on the same background that is brown. As described before, the dishes in the upper bar that we highlight contain less calories.

All features described above are combined in a 2 x 2 x 2 experimental design as shown in Table 6. The screens for all treatments are also shown in Appendix 3.

Table 6: Experimental design and sample size [a]

Treatment	**Order assistant**	**Traffic light labeling**	**Highlighting choices**	**N (total)**	**Females**
Treatment 1	0	0	0	49	25
Treatment 2	1	1	1	48	22
Treatment 3	1	0	0	51	25
Treatment 4	0	1	0	49	28
Treatment 5	0	0	1	50	32
Treatment 6	1	1	0	51	28
Treatment 7	0	1	1	53	27
Treatment 8	1	0	1	50	15
Total	200	201	201	401	199

[a] 1 (0) indicates feature is switched on (off), respectively.

5.3. Methodological approach

We model the choice outcome with an OLS regression where the dependent variable is the number of calories ordered, y_i. We assume that the calorie order depends on the presence of experimental features on the screen, sex of participants, level of self-control, calorie goal, and hunger level. Table 7 presents means and standard deviations of continuous and categorical variables included in the model.

Table 7: Description of variables included in the analysis

Variable	**Description**	**Mean (std. dev.)**		
		Full sample	**Men**	**Women**
Calories ordered (dependent variable)	The amount of kcal in the order	829.01 (307.67)	909.91 (289.34)	749.31 (305.03)
Calorie goal	Calorie goal entered by participants, default 700 kcal	768.58 (400.86)	864.32 (536.46)	674.26 (135.15)
Self-control	Self-control score[4]	42.12 (6.78)	41.47 (6.62)	42.76 (6.90)
Hunger	Hunger level, measured as 5-point Likert scale, where 1 – "not hungry at all" and 5 – "very hungry".	2.60 (1.30)	2.75 (1.31)	2.46 (1.27)

Table 7 shows that for the full sample calories ordered (829.01 kcal) considerably exceed the calorie goal (768.58 kcal), this holds also true for the sample split by sex. Women on average order 161 kcal less than men do ($p<0.01$), while their calorie goal falls 190 kcal below the one of men ($p<0.01$). The level of self-control differs only slightly and significantly between men and women ($p<0.10$). While 42.12 is the overall average, women (42.76) only slightly exceed men (41.47) in

[4] Self-control was measured using the 13 items of the scale by Tangney et al (2004) in its German translation provided in Bertrams & Dickhäuser (2009). The possible range of the scale is from 13 to 65.

this respect. Hunger level averaged at 2.6 for the whole sample, with hunger level being slightly higher (2.75) for men than for women (2.46) ($p<0.05$).

We estimate the following base model:

$$y_i = \beta_0 + \beta_1\, order\ assistant_i + \beta_2\, traffic\ light\ labelling_i + \beta_3\, highlighting\ choices_i + \beta_4\, self\text{-}control_i + \beta_5\, calorie\ goal_i + \beta_6\, hunger_i + \beta_7\, sex_i + u_i,$$

where $order\ assistant$, $traffic\ light\ labelling$, and $highlighting\ choices$ are binary variables taking the value of 1 if the feature is present on the screen and 0 otherwise; sex is a binary variable taking the value of 1 for women and 0 for men. We estimate this base model for the full sample and separately for each sex removing the sex dummy in the separate regressions. Next, we estimate a model to test our assumption that the level of self-control moderates the effectiveness of nudges:

$$y_i = \beta_0 + \beta_1\, order\ assistant_i + \beta_2\, traffic\ light\ labelling_i + \beta_3\, highlighting\ choices_i + \beta_4\, self\text{-}control_i + \beta_5\, calorie\ goal_i + \beta_6\, hunger_i + \beta_7\, sex_i + \beta_8\, order\ assistant_i * self\text{-}control_i + \beta_9\, traffic\ light\ labelling_i * self\text{-}control_i + \beta_{10}\, highlighting\ choices_i * self\text{-}control_i + u_i,$$

where $order\ assistant * self\text{-}control$, $traffic\ light\ labeling * self\text{-}control$ and $highlighting\ choices * self\text{-}control$ are interaction terms between features on the screen and self-control.

5.4. Analysis of Results

5.4.1. Results of the base model

We estimate OLS regressions for the full sample and the sample split by sex to determine the effectiveness of nudging features in reducing energy intake. For each model, we report standardized coefficients in addition to regression coefficients to be able to compare the level of influence of different independent variables (Table 8).

Table 8: Regression analysis [a]

Variables	Base model full sample			Base model split by sex					
					Men			Women	
	Coef.	Std. coef.	*p*	Coef.	Std. coef.	*p*	Coef.	Std. coef.	*p*
Order assistant	-106.27 (28.19)	-0.17	0.00	-61.07 (39.11)	-0.11	0.12	-156.84 (40.47)	-0.26	0.00
Traffic light labeling	13.10 (28.09)	0.02	0.64	-15.65 (38.77)	-0.03	0.69	51.12 (40.43)	0.08	0.21
Highlighting choices	8.26 (28.00)	0.01	0.77	46.01 (38.26)	0.08	0.23	-31.56 (40.38)	-0.05	0.44
Sex	-119.61 (29.11)	-0.19	0.00						
Self-control	-3.75 (2.08)	-0.08	0.07	-2.23 (2.92)	-0.05	0.45	-4.83 (2.93)	-0.11	0.10
Calorie goal	0.22 (0.04)	0.28	0.00	0.19 (0.04)	0.35	0.00	0.58 (0.15)	0.26	0.00
Hunger	31.73 (10.97)	0.13	0.00	37.37 (14.89)	0.17	0.01	22.47 (16.06)	0.09	0.16
Intercept	841.09 (99.62)		0.00	756.73 (133.43)		0.00	567.11 (175.69)		0.00
R^2		0.20			0.18			0.17	
N		398			196			202	

[a] Standard errors are reported in parentheses

Results of the base model demonstrate that the presence of the order assistant on the screen significantly negatively influences energy intake by 106.27 kcal. The sex of participants is also negatively related to energy intake and women compared to men have a lower amount of calories in the order by 119.61 kcal when controlling for the other variables. Another variable negatively related to energy intake is participants' level of self-control, meaning that a lower level of self-control is associated with higher energy intake. Calorie goal and hunger influence the amount of calories per order positively. The standardized coefficients in the model for the whole sample demonstrate the relative importance of the calorie goal and hunger in increasing energy intake compared to self-control.

When the regression is split by sex, the effects of the order assistant and the level of self-control are only significant for women. The presence of order assistant on the screen decreases the amount of calories in the order of women by 156.84 kcal. On the other hand, hunger only influences calorie intake by men and increases the amount of calories in the order by 37.37 kcal. The calorie goal entered before the order relates positively to energy order by both sexes. The importance of the calorie goal is underlined by the size of standardized coefficients for this variable as well (0.35 for men and 0.26 for women). The standardized coefficients also demonstrate relative importance of hunger (0.17) in increasing men's energy intake and the importance of self-control (-0.11) for women in decreasing energy intake.

Considering the relative importance of calorie goals, we investigate how many participants changed the default calorie goal entry of 700 kcal and in which direction.

Table 9: Calorie goal entries of participants

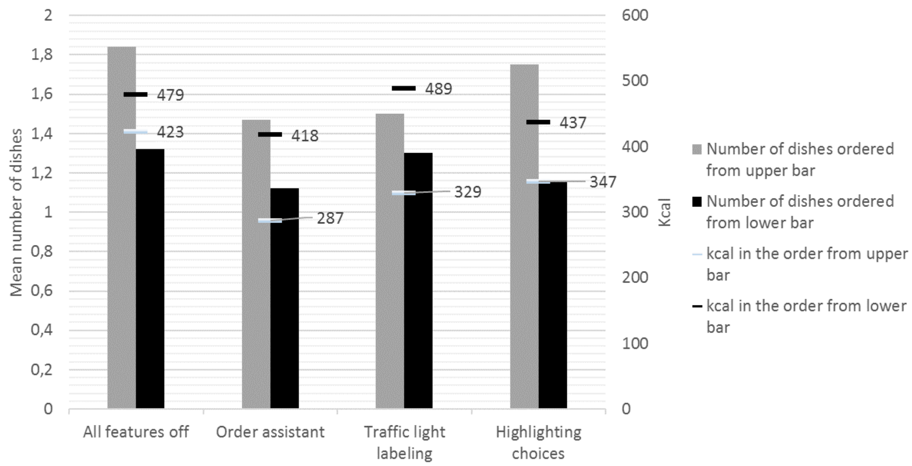
Calorie goal entries	Total (%)	Men (%)	Women (%)
Unchanged (700kcal)	295 (74%)	129 (65%)	166 (82%)
Changed	106 (26%)	70 (35%)	36 (18%)
- Change to more calories	63 (16%)	54 (27%)	9 (4%)
- Change to fewer calories	43 (11%)	16 (8%)	27 (13%)
N	401	199	202

Table 9 shows that the majority of participants did not enter a deviating calorie goal and maintained the default of 700 kcal. Notably, men changed the calorie goal almost twice as often as women did. There is a clear pattern in terms of the direction of the change: While the vast majority of men (54 out of 70) changing the calorie goal did so to more than 700 kcal, most women (27 out of 36) changed in the other direction. Thus, women aimed at decreasing energy intake even before facing the experimental treatments. That hunger significantly influenced the order of men but not of women may serve as an explanation for sex differences in goal setting. Another explanation comes from the influence of self-control, which negatively influences the amount of calories ordered by women but not by men.

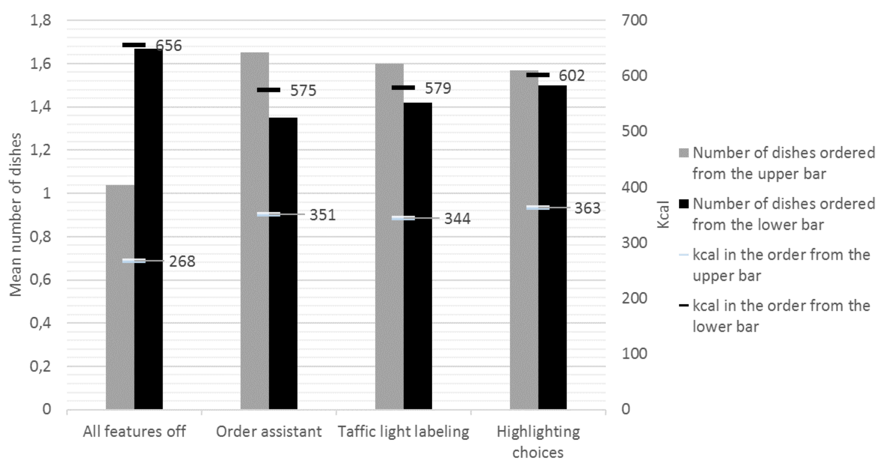
Women differ from men not only in terms of goal setting at the start of the experiment but also during the ordering process. We analyze the choice of dishes from upper vs. lower bar, i. e., low-calorie vs. high-calorie bar (bars are explained in the feature highlighting choices), and calculate the average number of dishes ordered from each bar in each feature including control treatment when all features are switched off (Figure 8a and 8b). The bars show the number of dishes ordered from the upper bar (grey) and the lower bar (black) while the dashes indicate the kcal from the items in the respective bars.

As shown in Figure 8a, women ordered fewer calories over all features, keeping the share of low calorie items from the upper bar relatively high compared to the lower bar. Men, on the other hand, ordered a higher share of items from the lower bar, which explains why their orders contain more calories on average. This difference is most prominent in the treatment when all features are switched off (see Figure 8a and 8b). Bearing in mind the fact that the order assistant is the feature where women ordered the lowest amount of calories, one pattern is of special interest: The smallest amount of food items ordered from the lower bar occurs in the feature order assistant. This is the case for men and women.

The observation that women order significantly less calories in this feature can be explained by them curtailing the number of high calorie items while maintaining the number of low calorie food orders. In contrast, males shift from high calorie to low calorie items (in comparison to the treatment with all features switched off), hence maintaining the total number of food items ordered at a comparable level. This increases the number of calories ordered by males in the feature order assistant to an extent that the effect of them ordering fewer high calorie food items from the lower bar is evened out. This is the reason for the order assistant not leading to a significant reduction of calories ordered for males but only for females.



8a: Women



8b: Men

Figure 8: Average number of dishes and the amount of calories ordered per bar and feature

The variable self-control also influences energy intake of different sexes differently. The coefficient in the base model for the full sample is negative and significant; however, when the model is split by sex, self-control only significantly affects the amount of calories ordered by women. To uncover the differences between men and women regarding levels of self-control we partition the sample into two groups (high self-control and low self-control) at the mean level of self-control variable of the full sample (42.12). Those with a below (above) average level of self-control are assigned to the group low (high) self-control. There are observable differences between men and women regarding levels of self-control (Table 10). While the low self-control group has a higher share of men, the high self-control group has higher share of women. As more women are characterized by higher level of self-control, it is not surprising that they have a lower amount of calories in their order

Table 10: Self-control levels by sex

Self-control levels and respective means	Men	Women	Total
Low (mean=36.31)	101	82	183
High (mean=47.00)	98	120	218
Total (mean=42.12)	199	202	401

5.4.2. Results of the model with interaction effects

Results of the previous estimations (Table 10) demonstrate that self-control has a significant and negative influence on the amount of energy per order in the estimations for the full sample and for women. To investigate if the level of self-control influences the effectiveness of nudging features we estimate models with interaction effects both for the whole sample and for men and women separately (Table 11).

Table 11: Regression analysis including interaction effects [a]

Variables	Full sample			Split by sex					
				Men			Women		
	Coef.	Std. coef.	*p*	Coef.	Std. coef.	*p*	Coef.	Std. coef.	*p*
Order assistant	-103.88 (28.22)	-0.17	0.00	-53.90 (39.36)	-0.09	0.17	-152.46 (41.01)	-0.25	0.00
Traffic light labeling	13.54 (28.07)	0.02	0.63	-14.76 (39.01)	-0.03	0.71	50.91 (40.86)	0.08	0.21
Highlighting choices	8.53 (28.00)	0.02	0.76	39.47 (38.46)	0.07	0.31	-24.84 (40.75)	-0.04	0.54
Sex	-119.15 (29.10)	-0.19	0.00						
Self-control [b]	-0.44 (4.17)	-0.01	0.92	-0.30 (5.76)	-0.01	0.96	0.22 (6.03)	0.00	0.97
Calorie goal	0.22 (0.04)	0.29	0.00	0.19 (0.04)	0.34	0.00	0.60 (0.14)	0.27	0.00
Hunger	30.83 (10.98)	0.13	0.01	36.12 (14.92)	0.16	0.02	22.79 (16.19)	0.09	0.16
Order assistant x self-control	1.38 (4.17)	0.02	0.74	6.84 (5.94)	0.11	0.25	-2.60 (5.89)	-0.04	0.66
Traffic light labeling x self-control	1.62 (4.19)	0.02	0.70	-0.68 (5.87)	-0.01	0.91	2.82 (6.01)	0.04	0.64
Highlighting choices x self-control	-8.58 (4.17)	-0.14	0.04	-9.04 (5.99)	-0.15	0.13	-9.07 (5.83)	-0.15	0.12
Intercept	682.04 (52.53)		0.00	667.19 (63.23)		0.00	340.96 (115.76)		
R^2		0.21			0.20			0.18	
N		398			196			202	

[a] Standard errors are reported in parentheses
[b] For the model with interaction terms, the variable self-control is mean centered to avoid collinearity (Enders & Tofighi, 2007; Dearing & Hamilton, 2006).

Results demonstrate that the only significant interaction occurs between self-control and the feature highlighting choices and decreases the amount of kcal in the order by 8.58. The standardized coefficient for this interaction indicates that the influence is rather low (-0.14) in comparison to other significant variables. However, when the sample is split by sex neither the variable self-control nor its interactions with nudging features are significant.

We turn to our sample split by the level of self-control to demonstrate different amounts of calories ordered in each nudging feature. In Table 12, we report average calorie levels in the fast food order corresponding to different levels of self-control for the whole sample and by features. Different levels of self-control lead to statistically significant differences in average energy intake between high and low self-control clusters across all treatments (p<0.10). Differences in means between low and high self-control groups are not significant at 5% level for the features order assistant and traffic light labeling. However, the feature highlighting choices results in significant mean differences (p<0.05), which means that participants from the high self-control group order significantly less calories than participants from the group with low self-control when the feature highlighting choices is used.

Table 12: Mean energy intake by participants with different levels of self-control

	Mean amount of kcal in the order		Mean difference amount of kcal in the order between the two clusters
	Low self-control	High self-control	
Whole sample	857.38	805.19	52.19
N	183	218	
Order assistant	813.70	760.48	53.21
N	92	108	
Traffic light labeling	863.01	791.13	71.88
N	87	114	
Highlighting choices	892.43	796.98	95.45
N	91	110	

5.5. Discussion

As a result of our experiment, the feature order assistant proved to be the most effective nudging intervention. It was the only feature that used facial expressions and messages as immediate feedback. Its influence, however, was significant only for women. Only limited evidence on sex differences in reaction to nudging interventions can be found in the literature. On the one hand, Missbach & König (2016) and Keller et al. (2015), who nudged participants to healthier choice using the position of food, did not find an effect of gender on the choice of snack bars. On the other hand, previous literature found that the mere presence of an animated interface agent enhances the effectiveness of communication for the screen user (Dehn & Van Mulken, 2000). Moreover, facial expressions in form of emoticons were demonstrated to influence perception of healthiness and taste of snack bars as reported by Vasiljevic et al. (2015). In their experiment, emoticons (especially with frowning expressions) were more effective than traffic light colored labels. A possible explanation for gender differences in the reaction to our order assistant is that men demonstrate worse performance in processing emotional facial expressions (Montagne et al., 2005), while women demonstrate greater ability to process positive facial expressions (Donges et al., 2012). Indicated differences in reactions to injunctive messages between men and women imply that the effectiveness of nudges including such messages can be conditional on sex.

Interestingly, women behaved differently not only during the ordering process but also when planning their energy intake as was indicated by differences in calorie goal settings. Women aimed for lower calorie intake from the start and continued by ordering mostly low calorie items. This effect can be explained by the fact that women give more importance to energy content of a fast food menu than men (Morse & Driskell, 2009) because food decisions in general are of greater personal importance and relevance for women than for men (Levi et al., 2006), possibly because of higher importance of personal appearance for women (Bates et al., 2009). Men, in contrast, tend to choose food items they perceive most satiating and prefer a beef burger menu over a healthier alternative (Lassen et al., 2016).

Another nudging feature that reduced the amount of calories ordered was highlighting choices. However, the influence was significant only in interaction with self-control. Highlighting choices was the only feature that did not provide immediate feedback to participants. As described before, this feature relies on the exploitation of present-biased preferences, i. e., it increases costs of choosing high-calorie items. In terms of decision-making, high calorie items on the screen have higher decision costs of being chosen than low-calorie items. At the same time, low-calorie items provide delayed rewards of not becoming overweight or obese. These rewards are only effective if a person can use self-control to delay gratification (O'Donoghue & Rabin, 1999). Consequently, self-control enables choosing delayed reward (not gaining weight) over immediate one (consuming high calorie food). Our results regarding the interaction between self-control and nudging elements point at the possible complexity of factors enabling the effectiveness of nudges, implying that not only socio-demographic but also psychological characteristics need to be taken into account when designing nudging interventions.

5.6. Conclusion

In this paper, we introduce modifications in a fast food order terminal to test the effectiveness of different nudging features including an order assistant, traffic light labeling and highlighting choices in lowering energy intake of young adults. Nudging is assumed to appeal to a simplified decision-making process in contrast to the mere provision of information, which assumes rational decision-making. Our results show that the order assistant is the only feature that leads to significantly fewer calories in the fast food order. The effect has strong a bias relating to biological sex. The amount of calories ordered was reduced for women but not for men. The level of self-control in interaction with the feature highlighting choices leads to lower calorie intake, however, this effect is rather small.

6. *ESSAY III:* Burgers and tears: The role of emotions in fast food choices of young adults [5]

Abstract

One of the reasons of higher calorie intake in young adults is the consumption of food away from home. A complex of situational and psychophysiological factors influences routine food choices. A gap in the literature exists regarding the influence of these factors on young adults with different BMI. A survey and an experiment have been developed to test the influence of situational and psychophysiological factors on the amount of calories ordered on an order terminal of a fast food restaurant for different BMI groups. Results demonstrate that BMI moderates some of the psychophysiological and situational factors. Subtler nudging modification mainly influenced overweight group of participants, when a regulating effect of self-control was only observed for the underweight group. Moreover, negative emotions increased the amount of calories in the order of underweight participants and decreased calories in the order of the overweight group.

Keywords: Young adults, food choices, emotions, BMI, nudging

[5] The paper was coauthored by Bernhard Mohr, Irina Dolgopolova, Carola Grebitus and Jutta Roosen. Bernhard Mohr designed the study, conducted the survey, performed the analyses and wrote the paper. Jutta Roosen provided advice on research design, data analysis and the development of the paper as well as editorial input.
Irina Dolgopolova and Carola Grebitus advised on data analysis, paper development and editing.

Submission status: Not submitted yet

6.1. Introduction

Rising obesity rates around the world draw attention to factors influencing food choices. Knowing these factors becomes crucial when obesity is understood as a result of individual choice (Bucher et al., 2016). Routine choices such as food choices are often made without elaborate decision-making and are prone to the influence of situational and psychophysiological factors (Cohen & Babey, 2012). Situational factors include physical surroundings of an individual during the process of a choice, while psychophysiological factors refer to psychological states (e. g., moods) and physiological states (e. g., feelings of thirst and/or hunger) (Mela, 2001). In addition, the physiological state of obesity is associated with the consumption of higher energy density foods and with experiencing more pleasure from food consumption (ibid.).

Among psychophysiological factors, emotions were identified as one important determinant of the amount of food consumed and the energy density of this food (Köster & Mojet, 2015). For example, Lyman (1982) demonstrated that positive emotions are mostly associated with the consumption of healthy foods while negative emotions are associated with junk food. Patel & Schlundt (2001) found that compared to a neutral emotional state both positive and negative emotions led to larger meals being consumed. Negative emotions were also linked to higher self-rated motivations to eat (Macht & Simons, 2000). On the other hand, positive emotions were found to be related to higher calorie consumption and snack intake (Bongers et al., 2013, Adriaanse et al., 2011). For normal weight and overweight participants both positive and negative emotions increased food intake, and this influence was even stronger for obese individuals (Canetti et al., 2002). In general, both negative and positive emotions have been linked to increased food consumption; however, the evidence on positive emotions is less conclusive (ibid.).

Emotions were also found to be related to body mass index (BMI). Barthomeuf et al. (2009) report that pictures of food evoking positive emotions differed only slightly between the groups of people with different BMI. However, obese participants, as compared to overweight and normal weight individuals, experienced negative emotions more often. In general, most research regarding the connection between BMI and food choices was focused on overweight individuals (Köster & Mojet, 2015). Geliebter & Aversa (2003) report relative undereating by underweight individuals and relative overeating by overweight ones when experiencing negative emotions. In response to positive emotions, underweight individuals reported eating more.

Recently, the discourse about obesity and possible measures to fight it is concentrated around choice architecture and nudging as possible moderators of food choice (Bucher et al., 2016). If we assume food choice to be influenced by a combination of situational and psychophysiological factors, then choice architecture and nudging represent a modification of situational factors. From psychophysiological characteristics, the combination of nudging and self-control (Rising & Bol, 2017) was discussed in the literature. Surprisingly little attention, however, has been paid so far to the effects of BMI on the effectiveness of nudging interventions. Bucher et al. (2016) reports only two studies that consider body weigh in the analysis of nudging interventions on healthier food choice in their systematic review. Both studies suggest that study subjects react to food positioning similarly, irrespective of body weight. In this paper, we fill the gap that still exists regarding the moderating role of BMI on calorie intake, considering situational and psychophysiological factors simultaneously.

Young adults are is at risk of developing obesity and staying obese at a later stage in life (Mensink et al., 2013). One of the underlying reasons is higher calorie intake in this age group caused by the consumption of food away from home (Nielsen et al., 2002). Additionally, regulating emotions is more difficult for young adults compared to older adults (Scheibe & Blanchard-Fields, 2009). Against this background, we investigate the role of psychophysiological and situational factors on energy intake among young adults using a fast-food ordering screen.

The remainder of the paper is as follows. The next section presents the experimental design and the data. Then, we present the data analysis. The last, fourth section discusses the results of the study and concludes.

6.2. Experiment and data

Participants

Participants of the study were 401 students from Technical University of Munich who received an incentive of 10 Euros. Subjects were between 17 and 26 years old with mean age of 19.5 years. Fifty percent of participants were female. They consumed fast food at least once a month with an average consumption frequency of five times per week.

Experiment

The experiment consisted of a pre-experiment questionnaire, a food order on a tablet screen that mimicked a fast food order terminal, and post-experiment questionnaire. The pre-experiment questionnaire asked participants to indicate their emotional state before the experiment, their level of feeling hungry, socio-demographic information, and information regarding their fast food consumption. Participants were then given a computer tablet with an interface similar to the one at a popular fast food restaurant in Germany. The first screen provided the opportunity to enter a calorie goal for the upcoming order with the default setting of 700 calories. 26% of participants changed the calorie goal while 74% remained with the default of 700 calories. Afterwards, participants saw the ordering screen (see Figure 9 for an example).

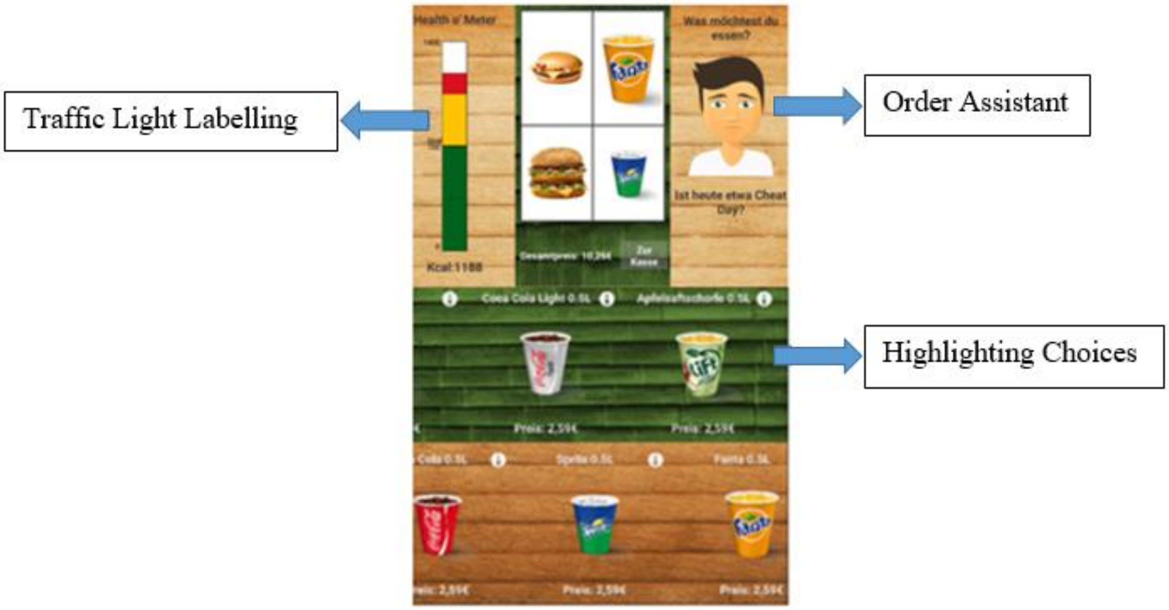


Figure 9: An example of ordering screen

Participants were randomly assigned to one of three experimental conditions, which included the presence on the screen (in combination with each other or separately) of an order assistant (OA), traffic light labeling (TLL), and highlighting choices (HLC) (Figure 9). The order assistant on the upper right screen aimed to influence the user by changing its facial expression depending on the current amount of calories in the shopping basket. The feedback given by the order assistant had five stages: neutral, friendly, critical, sad and shocked, all of these were accompanied by a respective message right below the assistant's face. Traffic light labeling was presented as a bar in the left upper corner of the screen, which changes color depending on calories in the shopping basket, from green to red. This was combined with a display of the number of calories below the graphical display. Highlighting choices occurred in the lower part of the screen, where the dishes to be selected by participants were organized in two sections: the upper (green) line contained 10 dishes with relatively little calories as small burgers, small fries, salads and diet drinks. The lower (brown) section contained food items and drinks with more calories. These measures together with the calorie goal setting at the start of the order comprise situational factors included in our experiment.

After completing the order on the screen, participants received the post-experiment questionnaire, which contained questions regarding their body mass index (BMI), self-control and if they are currently on a diet.

Measures of emotions, hunger, self-control and BMI

Emotional levels of participants were measured with the German version (Breyer & Bluemke, 2016) of the PANAS scale (Watson et al., 1988). The PANAS scale consists of 20 questions regarding specific emotions where the first ten questions refer to positive affect and the next ten to negative affect. Each emotion is rated on a 5-point Likert scale: 1 – very slightly or not at all; 2 – a little; 3 – moderately; 4 – quite a bit; 5 – extremely (Watson et al., 1988). Participants completed the set of questions before and after ordering the food to test whether the order affected their mood (e. g., by feeling guilty of having ordered too much).

Self-control was measured using the German version (Bertrams & Dickhäuser, 2009) of the self-control scale developed by Tangney et al. (2004). The short version of the scale used in the questionnaire contains 13 questions. Participants answered them using a 5-point Likert scale ranging from 1 – not at all to 5 – very much. We created a score of self-control for each participant by summing up the answers for all 13 questions and dividing the sum by 13. A higher score indicates a higher level of self-control.

Hunger was measured with the question: “How hungry are you at the moment?”, a 5-point Likert scale was used ranging from 1 - not at all hungry to 5 - very hungry.

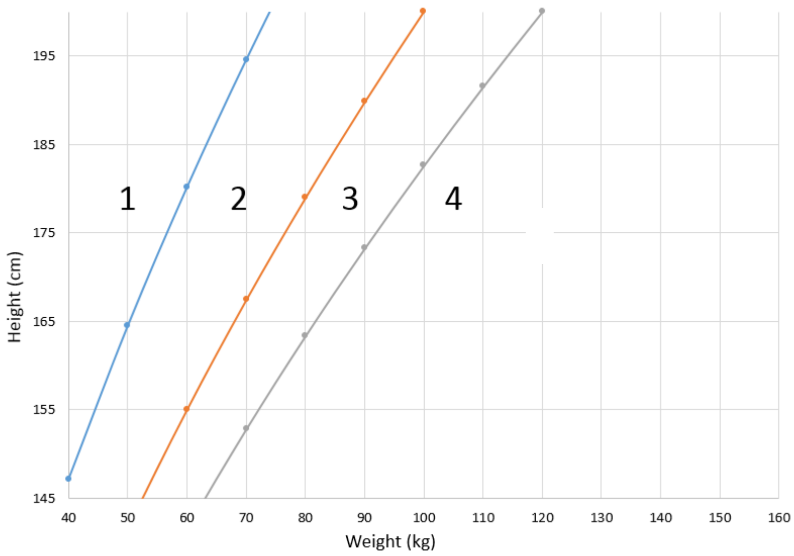


Figure 10: Graph used in the questionnaire for measuring BMI

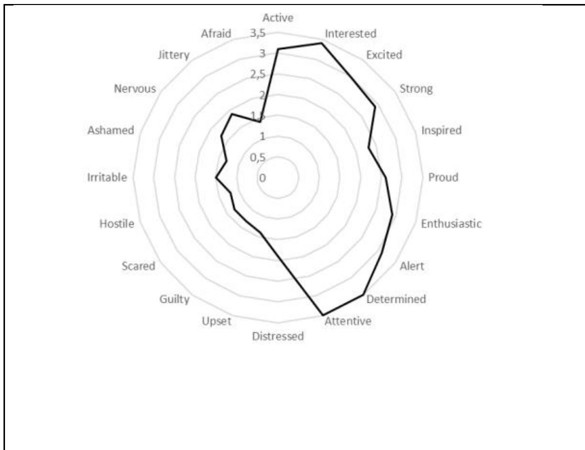
BMI was measured using the methodology suggested by National Heart, Lung, and Blood Institute[6], where four categories displayed in Figure 10 correspond to the following levels: 1 – underweight, 2 – normal weight, 3 – overweight, and 4 – obese. Participants also indicated if they are currently on a diet using a dummy variable, where 1 indicates being on a diet and 0 otherwise is used in the estimations.

6.3. Data analysis

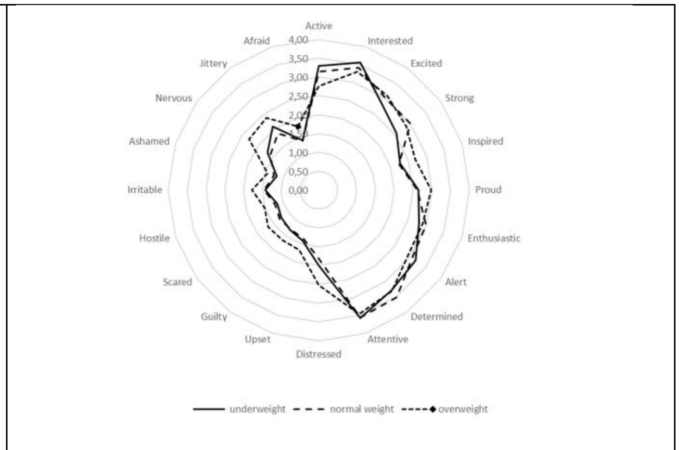
The distribution of participants regarding BMI is as follows: 49 participants are in category 1 (underweight), the majority (287) in category 2 (normal weight), 54 participants are in the category 3 (overweight), and only 4 participants in category 4 (obese). In the further analysis, we use only the first three categories.

[6] https://www.nhlbi.nih.gov/health/educational/lose_wt/BMI/bmi_tbl.htm

Levels of positive and negative emotions of participants before the ordering process are presented in Figure 11. In general, participants reported high levels of positive emotions and low levels of negative emotions (Figure 11a). When split by BMI, emotional levels appear to be rather similar for underweight and normal weight individuals, when for overweight participants the emotional levels are slightly higher negative emotions and some emotions in the positive spectrum.



11a. Emotional levels, total sample



11b. Emotional levels by BMI

Figure 11: Emotional levels of participants before and after the experiment

Table 13 below summarizes major characteristics of the sample, such as, calories ordered, calorie goal indicated before the order, BMI, self-control and hunger. The results are presented for the whole sample, as well as for the three identified BMI groups (underweight, normal weight and overweight.

Table 13: Descriptive statistics

		Mean (std. dev.)			
Variable	Description	Total sample (N=390)	BMI=1 (N=49)	BMI=2 (N=287)	BMI=3 (N=54)
Calories	Calorie level of the order	824.43 (308.85)	775.88 (287.37)	826.36 (312.88)	858.26 (306.13)
Goal	Self-selected calorie goal for the order	769.74 (406.29)	682.65 (158.62)	782.23 (441.78)	782.41 (357.16)
Female	1 – if individual is a woman, 0 - otherwise	0.51 (0.50)	0.81 (0.39)	0.49 (0.50)	0.31 (0.47)
BMI	1 – lowest, 4 - highest	2.01 (0.51)	---	---	---
Self-control	Summary score based on 13 questions	42.11 (6.84)	43.37 (8.14)	42.02 (6.66)	41.43 (6.47)
Hunger	1 – not at all, 5 – very much	2.59 (1.30)	2.43 (1.24)	2.60 (1.30)	2.71 (1.33)
Diet	1 – being on a diet, 0 – otherwise.	0.11 (0.31)	0.08 (0.28)	0.10 (0.30)	0.20 (0.41)

The average level of calories ordered differs between groups of participants according to BMI category, with the lowest amount of calories ordered by the underweight group and the highest by the overweight group. Underweights also set the lowest average calorie goal for the order, when calorie goals of normal weight and overweight participants were almost equal. While the whole sample is split equally between genders, the majority of underweight participants are female and the majority of overweight participants are male. Self-control scores differed slightly among BMI groups with underweight participants having the highest average level of self-control and overweight participants having the lowest level of self-control. Levels of hunger were also highest for the overweight group and lowest for the underweight one. Most participants on a diet were among the overweight group.

To assess the influence of emotions on the calories ordered, exploratory factor analysis was performed using STATA 13.1 on 20 questions regarding positive and negative emotions from the

PANAS scale. We report the results of factor analysis in Table 14 (bold items are used in the interpretation of the respective factor).

Table 14: Varimax rotated factor loadings for emotions before the ordering process

	1 Negative	2 Positive	3 Active
Active	-.1585	.3872	**.5267**
Interested	-.2715	**.5512**	.3893
Excited	-.0559	**.7164**	.1790
Strong	-.0921	**.4377**	.4088
Inspired	.2712	**.5807**	-.1398
Proud	.1421	**.6742**	-.0327
Enthusiastic	.0481	**.7532**	.1815
Alert	-.0135	-.0036	**.7422**
Determined	-.0684	.3053	**.6054**
Attentive	-.0568	.1042	**.7549**
Distressed	**.6435**	.0703	.0963
Upset	**.8035**	-.0668	-.0017
Guilty	**.8322**	-.0099	.0102
Scared	**.7984**	-.0016	.0261
Hostile	**.7986**	-.0187	-.0019
Irritable	**.7608**	-.0136	-.1310
Ashamed	**.8402**	-.0515	-.0763
Nervous	**.7343**	.1962	.1295
Jittery	**.6294**	.1481	-.2673
Afraid	**.7854**	.0393	-.1496

Three factors were identified, which describe negative, positive and active emotions experienced by participants before the experiment. The "negative" factor includes all 10 negative emotions. The "positive" factor includes emotions as interested, excited, strong, inspired while the "active" factor includes emotions as active, alert, determined, and attentive. Cronbach's α for the three factors is: $\alpha = 0.92$ for "negative" factor, $\alpha = 0.72$ for "positive" factor and $\alpha = 0.68$ for "active" factor. The related factor scores are used in the subsequent analysis.

We assume a linear relationship between the level of calories ordered, psychophysiological characteristics of participants (sex, self-control, BMI, hunger emotions) and situational factors (calorie goal and experimental conditions). The following model is estimated:

$$Cal_i^* = x_i\beta + \varepsilon_i,$$

where x_i is a vector of psychophysiological and situational factors, Cal_i^* is a latent variable denoting the amount of calories in the order and $\varepsilon_i \sim N(0, \sigma^2)$. Cal_i^* is not observed below 200 calories and above 2000 calories, thus reflecting the realistic amount of calories in a fast food order. We estimate Tobit with upper and lower limits, where

$$Cal_i^* = \begin{cases} 200 \; if \; Cal_i \leq 200 \\ Cal_i \; if \; 200 < Cal_i < 2000 \\ 2000 \; if \; Cal_i \leq 2000. \end{cases}$$

Results of the estimations are presented in Table 15. We estimate four models: one for the whole sample, and three models for each of the BMI groups.

Table 15: Model estimation for the whole sample, and three models for each of the BMI groups

	Total sample	Underweight	Normal weight	Overweight
Variable	Marginal effects (std. err.)			
Situational factors				
OA	-110.86*** (27.70)	-109.69* (60.38)	-106.87*** (33.07)	-145.13* (74.84)
TLL	18.41 (27.48)	6.79 (57.96)	40.28 (32.87)	-103.58 (71.87)
HLC	1.43 (27.59)	54.38 (57.85)	13.52 (32.95)	-161.17** (76.51)
Goal	0.21*** (0.03)	0.13 (0.18)	0.20*** (0.04)	0.25** (0.10)
Psychophysiological factors				
Female	-112.04*** (29.77)	-265.71*** (79.29)	-96.50*** (34.14)	-240.49** (100.11)
Self-control	-3.68* (2.09)	-10.79*** (3.85)	0.16 (2.55)	-7.02 (6.39)
BMI	15.38 (28.13)	---	---	---
Hunger	30.56*** (10.75)	62.12*** (23.14)	24.40* (12.75)	35.23 (26.61)
Diet	-76.45* (44.75)	-135.90 (102.29)	-111.68** (54.87)	54.27 (102.18)
Negative	-8.60 (14.71)	76.61** (36.16)	-8.92 (18.89)	-53.03* (27.89)
Positive	9.74 (13.98)	-14.70 (29.99)	8.61 (16.70)	17.68 (35.52)
Active	-9.46 (14.34)	-7.66 (30.14)	-16.59 (16.98)	10.22 (39.09)
N of obs.	386	49	285	52

OA=Order assistant, TLL=Traffic light labeling, HLC, Highlighting calories, E=Emotions
*** refers to 0.01 significance level, ** to 0.05 and * to 0.10 significance levels respectively
Price is not included as it is highly correlated with calories ordered and the choice was hypothetical

Looking at the results for the whole sample, we find that both situational and psychophysiological factors influenced the amount of calories in the fast food order. From situational factors, the presence of the order assistant decreased the amount of calories in the order by 110.86 kcal, while the calorie goal set before the order influenced the amount of calories positively. From psychophysiological factors, being a female negatively influenced the amount of calories ordered

(-112.04 kcal). The level of hunger influenced the amount of calories ordered positively (30.56 kcal). Being on a diet decreased the amount of calories in the order by 76.45 kcal.

When the sample is split by BMI level, more interesting results can be observed. First, the order assistant remained an effective on-screen communication method that led to a decrease in the amount of calories ordered for all three groups. The effect was strongest for overweight individuals. Second, for overweight individuals, another effective method of on-screen communication is highlighting choices. Calorie goal is another situational factor influencing the amount of calories in the order for normal weight and overweight participants. From psychophysiological factors, being female reduced ordered calories in all of the groups, and hunger was a significant factor for underweight and normal weight groups. Being on a diet significantly decreased calories in the orders of normal weight participants. Interestingly, negative emotions led to an increase in calories ordered by underweight participants by 76.61 kcal, while for overweight participants, negative emotions led to a decrease of calories in the order (-53.03 kcal). For the majority of participants in the normal weight group, neither positive nor negative emotions played a significant role in the choice of food options.

6.4. Conclusion and discussion

Overall, a combination of situational and psychophysiological factors was found to influence the amount of calories in fast food orders of young adults. From situational factors, the order assistant was a successful on-screen communication for the whole sample and for all BMI groups. Splitting the sample by BMI did not change the direction of the effect of the order assistant, which indicates that BMI does not moderate the effectiveness of this nudging intervention. This result is in line with previous evidence on nudging among different body weight groups provided by Bucher et al. (2016). Highlighting choices resulted in lowering calories ordered only for overweight participants.

It is possible to assume that being sensitive about their weight, overweight participants react to subtler ques than other BMI groups. While the order assistant provides direct and straightforward feedback by demonstrating either approval (with a smile) or disapproval (with a frown) depending on the amount of calories in the order, highlighting choices exploits present-biased preferences by making low-calorie food choice more prominent on the screen and thus requiring less effort to order. Overweight participants, being the only group influenced by highlighting choices, might be more sensitive to this kind of nudging interventions; however, further evidence is needed to support this assumption.

From psychophysiological factors, being female resulted in a significant decrease of calories ordered for the whole sample and for all the BMI groups. The effect was most prominent for underweight and overweight participants. Women tend to pay more attention to and to use calorie information more than men (Gerend, 2009). Our results demonstrate that this effect spreads across all BMI groups indicating that gender effect is not moderated by BMI. One possible explanation is that women tend to overestimate their perceived weight in all BMI groups (Wardle et al., 2006).

As we assume food choices to be rather automatic, routine decisions, self-control becomes an important factor influencing the outcome of these decisions. When self-control is low, there are higher chances that information related to caloric intake is ignored. Our results indicate that the presence of self-control reduces the amount of calories in the order, however, when the sample is split by BMI groups, this effect is only significant for the underweight group. Crescioni et al. (2011) relate self-control not only to fewer calories consumed but also to the weight of individuals. For the underweight group of young adults in our sample, a higher level of self-control does not only predict less calories in the order but also being in the underweight group in the first place.

While the emotional factors we identified do not show significant effects for the whole sample, we find an effect for the "negative" factor when splitting the sample by BMI, which leads to a considerable increase in calories ordered for underweight participants (68 calories) while there is a significant decrease for overweight participants (56 calories). This finding is in line with previous research. Barthomeuf et al. (2009) report that the intensity of negative as well as positive emotions felt towards food pictures differs in adolescents depending on their BMI. To be more exact, they find that the intensity of negative emotions towards desirable foods was higher in the obese than in overweight and normal-weigh participants. Although our sample only contained 4 participants who can be classified as obese, we find the same tendency as the above cited authors for overweight participants.

Overall, we find that BMI moderates some of the psychophysiological and situational factors. The subtler nudging modification of highlighting choices mainly influenced overweight participants, while the regulating effect of self-control was only observed for underweight participants. Moreover, negative emotions increased the amount of calories in the order of underweight participants and decreased calories in the order of overweights. This evidence sheds new light on the role of BMI and emotions in fast food choice in the presence of nudging interventions.

7. Discussion, implications and limitations

While this thesis found dynamic feedback on digital devices successfully making consumer information more available, there are also other voices emphasizing the downsides of the increased use of digital devices in everyday lives. Clearly, a consequence of the dissemination of digital devices as smart electricity meters and ordering food at an ordering screen would further increase the frequency of use of digital devices. This could have negative effects as risks of an increased use of digital media especially for children and young adults include negative health effects on sleep, attention, and learning as well as rising obesity rates and depression (Chassiakos et al., 2016).

The dynamic feedback measures used in experiment II are subject to another stream of criticism, namely that they are paternalistic. The criticism here is that the "designer" of the information tool defines the desirable behavioral outcome, i. e., which behavior the information tool is to change into which direction. This criticism was picked up by behavioral scientists and countered with the concept of "libertarian paternalism". It is defined as trying "to influence choices in a way that will make choosers better off, as judged by themselves" (Thaler & Sunstein, 2008, p. 5). But still, critics ask, who can arrogate himself to decide about what are good and what are bad choices (Bruttel et al., 2014)?

Further critical questions on this issue are in which cases exactly altering choices is justifiable, and on what basis the justification to do so can be made, meaning on what time horizon or welfare judgement and based on which concept of rationality. These questions largely remain unanswered which is critical as nudging measures and other practical implications from behavioral economics increasingly are in the focus of policy makers, also in Germany (ibid.). Worth of critical discussion is also the question of how sustainable the behavioral changes are that can be expected from the information tools tested in this dissertation as previous research found them to decay over time (Allcott, 2011) or largely vary over population groups (Ehrhardt-Martinez & Donnelly, 2010). Further field research is needed to improve the design of information tools so that they constantly can make consumer information more available. To be able to do so, further research is also needed on the reasons for the superiority of the feedback instrument order assistant found in this dissertation. Previous research remained rather vague by outlining that an animated interface agent enhances the effectiveness of communication (Dehn & Van Mulken, 2000). Another open question is if it was rather the affirmative signal of the happy faces that made participants change their order behavior in essay I or the restrictive or punishing signal of the unhappy face (and respective message). Previous research found especially frowning expressions effective (Vasiljevic et al., 2015). Finally, more research is needed to shed light on the varying ability of information tools to make consumer information more available depending on psychophysiological factors that was found in this dissertation. In the following, implications for policy, management and research from the presented experimental results shall be given, specifically to application and for each essay separately.

In essay I, an experiment was set up to find out which information tools consumers are willing to use, while each of these contained a different kind of dynamic feedback. The information tools at stake in essay I concerned energy consumption patterns and related issues displayed on a smart electricity meter. For a better explanation of the key results, again, a list of the respective information tools shall be given. Its first ranks were preferred most by participants.

(1) Automatic switch-on if reduced tariff available, (2) Traffic light signal if reduced tariff available (3) Consumption display by time, rooms & devices, (4) Consumption display by time, (5) Consumption display by time & rooms. Essay I further shows that consumers are critical about data protection issues which scored negative preferences while a technical solution for increased data protection was relatively unpopular but still positively valued.

That the information tools on ranks 1 and 2 both contain dynamic feedback depending on the current net load (see chapter 2.4.3.) implies that consumers prefer feedback on current net load over feedback on individual consumption patterns provided by the information tools that scored ranks 3,4 and 5. One possible explanation for this result is that only the information tools on current net load enable the consumer to benefit from reduced electricity tariffs (see chapter 2.4.3.). The most popular information tool, the automatic switch-on if a reduced tariff is available does so while it requires relatively little behavioral change from the user as the switch-on is automatized. Saving electricity and money, respectively, requires more effort when relying on information tools 3, 4 and 5 displaying individual consumption patterns. Noteworthy, among these, the information tool providing the most detailed information on consumption patterns was the most popular one.

It can be concluded that those information tools enabling consumers to save money and electricity with relatively little effort were preferred over those where more behavioral change in everyday life was needed. Another implication for the design of information tools which can be derived from the experimental results of paper I is that consumers do not oppose to relatively complex information tools. In the case of dynamic feedback dependent on current net load, the involved complexity comes from understanding the rather complex interplay between smart grid and smart meter as well as the interconnection between smart meter and smart household devices. Results concerning dynamic feedback on individual consumption patterns point to the same direction: The most complex consumption display was liked most by participants compared to less complex alternatives. This is why essay I implies that producers should not underestimate consumers' willingness to use complex information tools.

More generally speaking, essay I implies that consumers are highly willing to accept and use information tools containing dynamic feedback measures also and probably especially in a field where the technological background brings some complexity with it. It is especially those complex cases where information tools can help to make consumer information more available where otherwise information would have been hard to access. Despite accepting complexity, consumers value information tools requiring little behavioral change in everyday life over others. The crucial role of smart electricity meters in the German energy turnaround was pointed out in chapter 2.4.4. Along with expected electricity savings, this provides a solid ground to recommend a legal basis for the installation of smart electricity meters also for smaller households and to increase legislative efforts to bring net load flexible electricity tariffs to the German electricity market. Another recommendation for policy – as well as management – is to carefully treat the sensitive issue of data protection, by being transparent about which data information tools produce and store at what time and how the respective data is protected. Who exactly can access it at what times for what purpose and whom it belongs to are further sensitive issues that should be communicated clearly to consumers. The same holds true for radiation produced by new information tools while consumers were found to distrust technological measures to reduce radiation in essay I so that such measures will not lead to more acceptance on the side of the consumer.

As Sovacool (2014) already pointed out, human choice is dramatically underrepresented in energy research. This is also the case for information tools using dynamic feedback, and not only in energy research. More research is needed to see if the results found in essay I of this dissertation can be applied to other technological devices and topical domains, but also to shed light on the underlying motives of the preferences found for certain information tools.

Essays II examines how three given information tools, i. e., manipulations on a fast food ordering screen are able to change consumer behavior when being applied during the usage situation. This was achieved by elaborating which (combinations of) information tools were able to lower calories ordered in the target group of young adults.

Key findings of essay II imply that personally appealing dynamic feedback in the form of an order assistant is more effective in changing behavior than other kinds of dynamic feedback, namely traffic light labelling and highlighting choices. The personally appealing feedback in the form of an order assistant did, however, show its effect exclusively for women. Further results involve the share of high-caloric dishes ordered by men vs. women. A gender effect was also found when analyzing the role of calorie goal setting. Also, a moderating effect of self-control was found for the condition ‘highlighting choices’. It can be concluded that many psychophysiological factors influence the observed ability of the tested information tools to lower calories ordered. These need to be taken into account so that any information tool can successfully make consumer information more available or influence consumer behavior, more generally speaking. Results of essay II further show that men and women react differently to information tools. Therefore, in some cases, designing separate information tools for men and women or population subgroups is advisable.

This implies that management and designers should thoroughly test information tools with different groups of consumers. Policy makers using insights from behavioral economics should do so, too. A key implication is that personally appealing feedback is to be preferred over information tools with no personal appeal. As relatively little research has been performed so far on information tools using dynamic feedback measures, further studies are needed to replicate the results from essay II to other consumer decision areas.

Essay III, relating to the same experimental data as essay II, examines the complex of situational and psychophysiological factors influencing food choices. Gender, calorie goal, self-control, hunger, being on a diet, emotional state and BMI were found to influence the efficiency of experimental conditions on the screen to lower calories ordered. Furthermore, moderating effects were identified. For females, the presence of the order assistant lowered calories ordered in all BMI groups, i. e., for these variables there was no moderating effect of BMI. Highlighting, by contrast, only influenced overweight participants. Many psychophysiological factors involved in the respective analyses were also moderated by BMI.

However, BMI was found to have an effect on how calorie goal, self-control, hunger, being on a diet and negative emotions affect calories ordered in the experiment. Self-control was only found to play a role for the group of underweight individuals when ordering fast food. This implies that information tools could be positioned to influence some of the named influencing factors, e. g., self-control but also that this only will be effective if the interplay with other involved variables is understood and taken into account.

Again, further research is needed to disentangle the influences different factors have on the efficiency of information tools using dynamic feedback to make consumer information more available. The upper list of psychophysiological factors can help to design future experiments. For management, essay III implies that designing different information tools for different BMI groups or depressive consumers, to name two examples, may be promising ways to improve information tools using dynamic feedback. However, the strength of the results of essays II and III would need to be double-checked in future studies with a higher number of participants before definite and clear recommendations for management can be given. Policy makers should increase their efforts to examine the practical application of measures from behavioral economics, e. g., by creating own information tools.

Besides the fact that a higher number of participants would be necessary to ensure representativeness of results, another limitation of the doctoral thesis at hand concerns the transferability of results of essays I, II and III. Future series of experiments on this topic should replicate studies for different consumer decision areas rather than changing consumer decision area and research scope at the same time as this dissertation did in experiments I and II. Another limitation is that the goods used in the two experiments forming this thesis are of different kind. The electricity meter is a durable good while food is a consumable. The problem here is that the way consumption decisions for these kind of goods are made differ in many respects, which makes it harder to transfer findings across experiments. A limitation that exclusively applies for experiment I is that it only recorded the final amount of calories ordered. Future experiments should document more of consumers' behavior, i. e., if participants did withdraw calories from the shopping basket and at what time they did so.

8. Overall conclusion

Summing up the results from the three essays, it can be concluded that consumers are indeed willing to use information tools containing dynamic feedback elements. It was also shown that such information tools have an impact on subsequent choices. Which practical implications can be drawn from a closer look at the experimental results was outlined in the previous chapter 7. The present chapter aims to give a more general overview of the findings, especially concerning consumer information, i. e., how this dissertation can contribute to making consumer information more available.

Although, as outlined, experiments I and II differ concerning research scope and consumer decision area, some conclusions can be drawn from their results that also apply to other decision areas. This is the case for consumers' sensitivity to data protection issues found for smart meters in experiment I. It is especially the decision area of food where the use of personal data might lead to a large increase in efficiency of information systems aiming at changing dietary patterns. This will only work if consumers do not doubt data protection issues bring taken seriously, especially as food-related personal data as BMI is even more sensitive than energy consumption patterns.

Furthermore, information tools can be expected to be accepted by consumers when holding the following features: avoiding radiation, being convenient by avoiding efforts to change everyday behavior on the side of the user as far as possible and making complex networks or other patterns graspable. They are more likely to indeed make consumer information more available when using personally appealing feedback and when influencing variables are controlled for, or insights on influencing variables are used to design different information tools for different population subgroups.

Results from experiment II can also be generalized to other consumer decision areas, namely that dynamic feedback using facial expressions can make consumer information more available and influence consumers' decisions. Smiley faces on electricity bills showed an effect on the amount of electricity consumed in previous literature so that it seems fruitful to apply dynamic feedback using facial expressions devices like smart electricity meters or the increasing number of health-related apps. The variety of influencing psychophysiological variables found in experiment II shows that the complex combination of influencing factors coming from environmental influences and individual differences, moods and emotions should be carefully considered when designing measures to make consumer information more available, or, more generally speaking, change consumer behavior using insights from behavioral economics.

References

Abicht, L., & Spöttl, G. (2012). *Qualifikationsentwicklungen durch das Internet der Dinge: Trends in Logistik, Industrie und" Smart House"*. Bielefeld: W. Bertelsmann Verlag.

Adriaanse, M. A., de Ridder, D. T. D., & Evers, C. (2011). Emotional eating: Eating when emotional or emotional about eating? *Psychology & Health*, *26*(1), 23–39. https://doi.org/10.1080/08870440903207627

Allcott, H. (2011). Social norms and energy conservation. *Journal of Public Economics*, *95*(9–10), 1082–1095. https://doi.org/10.1016/J.JPUBECO.2011.03.003

Allison, D. B., Fontaine, K. R., Manson, J. A. E., Stevens, J., & VanItallie, T. B. (1999). Annual deaths attributable to obesity in the United States. *Journal of the American Medical Association*, *282*(16), 1530–1538. https://doi.org/10.1001/jama.282.16.1530

Allman-Farinelli, M. (2015). Nutrition Promotion to Prevent Obesity in Young Adults. *Healthcare*, *3*(3), 809–821. https://doi.org/10.3390/healthcare3030809

Ariely, D. (2008). *Predictably irrational : the hidden forces that shape our decisions*. New York: Harper.

Arno, A., & Thomas, S. (2016). The efficacy of nudge theory strategies in influencing adult dietary behaviour: A systematic review and meta-analysis. *BMC Public Health*, *16*(1), 1–11. https://doi.org/10.1186/s12889-016-3272-x

Ballantine, W. B. (2005). Effects of interactivity and product information on consumer satisfaction in an online retail setting. *International Journal of Retail & Distribution Management*, *33*(6), 122–132. https://doi.org/https://doi.org/10.1108/09590550510600870

Baron, J. (2010). Review of Nudge: Improving decisions about health, wealth, and happiness. *Journal of Behavioral Decision Making*, *23*(2), 224–226. https://doi.org/10.1002/bdm.652

Barringer, F. (2011, January 30). New electricity meters stir fears. *The New York Times*, p. A12.

Barthomeuf, L., Droit-Volet, S., & Rousset, S. (2009). Obesity and emotions: Differentiation in emotions felt towards food between obese, overweight and normal-weight adolescents. *Food Quality and Preference*, *20*(1), 62–68. https://doi.org/10.1016/j.foodqual.2008.07.005

Bates, K., Burton, S., Howlett, E., & Huggins, K. (2009). The roles of gender and motivation as moderators of the effects of calorie and nutrient Information Provision on Away-from-Home Foods. *Journal of Consumer Affairs*, *43*(2), 249–273. https://doi.org/10.1111/j.1745-6606.2009.01139.x

Bearden, W. O., Netemeyer, R. G., & Mobley, M. F. (1993). *Handbook of marketing scales : multi-item measures for marketing and consumer behavior research*. Newbury Park, California: Sage Publications.

Beniger, J. R. (James R. (1986). *The control revolution : technological and economic origins of the information society*. Cambridge: Harvard University Press.

Bertrams, A., & Dickhäuser, O. (2009). Messung dispositioneller Selbstkontroll-Kapazität: Eine deutsche Adaptation der Kurzform der Self-Control Scale (SCS-K-D). *Diagnostica, 55*(1), 2–10. https://doi.org/10.1026/0012-1924.55.1.2

Biervert, B., Fischer-Winkelmann, W. F., & Rock, R. (1977). *Grundlagen der Verbraucherpolitik: gesamt- u. einzelwirtschaftl. Analyse*. Reinbek: Rowohlt.

Blanchemanche, S., Marette, S., Roosen, J., & Verger, P. (2010). 'Do not eat fish more than twice a week'. Rational choice regulation and risk communication: Uncertainty transfer from risk assessment to public. *Health, Risk & Society*, *12*(3), 271–292. https://doi.org/10.1080/13698571003710340

Bleich, S. N., Economos, C. D., Spiker, M. L., Vercammen, K. A., VanEpps, E. M., Block, J. P., … Roberto, C. A. (2017). A Systematic Review of Calorie Labeling and Modified Calorie Labeling Interventions: Impact on Consumer and Restaurant Behavior. *Obesity*, *25*(12), 2018–2044. https://doi.org/10.1002/oby.21940

Bolduc, D. (2008). Hybrid Choice Modeling of New Technologies for Car Use in Canada. *Transit*, (418), 1–18.

Bongers, P., Jansen, A., Havermans, R., Roefs, A., & Nederkoorn, C. (2013). Happy eating: The underestimated role of overeating in a positive mood. *Appetite*, *67*, 74–80. https://doi.org/10.1016/j.appet.2013.03.017

Breuer, G. (1998). *Frauenbewegung im Katholizismus : der Katholische Frauenbund 1903-1918*. Frankfurt am Main: Campus Verlag.

Breyer, B., & Bluemke, M. (2016). *Deutsche Version der Positive and Negative Affect Schudule PANAS (GESIS Panel). Zusammenstellung sozialwissenschaftlicher Items und Skalen*. Mannheim: GESIS - Leibniz Institute for the Social Sciences. https://doi.org/10.6102/zis242

Brodie, M. L., Mylopoulos, J., & Schmidt, J. W. (1984). *On Conceptual Modelling : Perspectives from Artificial Intelligence, Databases, and Programming Languages*. Springer New York.

Bruttel, L. V., Stolley, F., Güth, W., Kliemt, H., Bosworth, S., Bartke, S., … Funk, L. (2014). Nudging als politisches Instrument — gute Absicht oder staatlicher Übergriff? *Wirtschaftsdienst*, *94*(11), 767–791. https://doi.org/10.1007/s10273-014-1748-9

Bucher, T., Collins, C., Rollo, M. E., McCaffrey, T. A., De Vlieger, N., Van Der Bend, D., … Perez-Cueto, F. J. A. (2016). Nudging consumers towards healthier choices: A systematic review of positional influences on food choice. *British Journal of Nutrition*, *115*(12), 2252–2263. https://doi.org/10.1017/S0007114516001653

Bundesregierung. (2016). Gesetz zur Digitalisierung der Energiewende. *Bundesgesetzblatt*, *2016*(43), 2034–2064. Retrieved from https://www.bmwi.de/BMWi/Redaktion/PDF/Gesetz/gesetz-zur-digitalisierung-der-energiewende,property=pdf,bereich=bmwi2012,sprache=de,rwb=true.pdf

Canetti, L., Bachar, E., & Berry, E. M. (2002). Food and emotion. *Behavioural Processes*, *60*(2), 157–164. https://doi.org/10.1016/S0376-6357(02)00082-7

Cascetta, E. (2009). *Transportation Systems Analysis, Models and Applications*. *Transportation Research* (Vol. 10). Berlin: Springer Verlag. Retrieved from https://link.springer.com/content/pdf/10.1007%2F978-0-387-75857-2.pdf

Cavoukian, A., Polonetsky, J., Wolf, C., Cavoukian, A., Polonetsky, J., & Wolf, : C. (2010). SmartPrivacy for the Smart Grid: embedding privacy into the design of electricity conservation. *Identity in the Information Society*, *3*(2), 275–294. https://doi.org/10.1007/s12394-010-0046-y

CDU, CSU, & FDP. (2009). *Wachstum. Bildung. Zusammenhalt. Koalitionsvertrag zwischen CDU, CSU und FDP. 17. Legislaturperiode*. Berlin: Bundesdruckerei. Retrieved from http://www.kas.de/upload/ACDP/CDU/Koalitionsvertraege/Koalitionsvertrag2009.pdf

CDU, CSU, & SPD. (2005). *Gemeinsam für Deutschland. Mit Mut und Menschlichkeit. Koalitionsvertrag zwischen CDU, CSU und SPD. 16. Legislaturperiode.* Berlin: Bundesdruckerei. Retrieved from https://www.bundesregierung.de/Content/DE/_Anlagen/koalitionsvertrag.pdf?__blob=publicationFile&v=2

CDU, CSU, & SPD. (2013). *Deutschlands Zukunft gestalten. Koalitionsvertrag zwischen CDU, CSU und SPD. 18. Legislaturperiode*. *Bundesregierung*. Berlin: Bundesdruckerei. https://doi.org/Koalitionsvertrag

CDU, CSU, & SPD. (2018). *Ein neuer Aufbruch für Europa Eine neue Dynamik für Deutschland Ein neuer Zusammenhalt für unser Land. Koalitionsvertrag zwischen CDU, CSU und SPD. 19. Legislaturperiode*. *Deutscher Bundestag*. Berlin: Bundesdruckerei. https://doi.org/Koalitionsvertrag

Chen, R., Smyser, M., Chan, N., Ta, M., Saelens, B. E., & Krieger, J. (2015). Changes in awareness and use of calorie information after mandatory menu labeling in restaurants in King County, Washington. *American Journal of Public Health*, *105*(3), 546–553. https://doi.org/10.2105/AJPH.2014.302262

Chevalier, J. A., & Mayzlin, D. (2006). The Effect of Word of Mouth on Sales: Online Book Reviews. *Journal of Marketing Research*, *43*(3), 345–354. https://doi.org/10.1509/jmkr.43.3.345

Cohen, D. A., & Babey, S. H. (2012). Contextual Influences on Eating Behaviors: Heuristic Processing and Dietary Choices. *Obesity Review*, *13*(9), 766–779. https://doi.org/10.1111/j.1467-789X.2012.01001.x.Contextual

Cooke, P. (2001). Regional Innovation Systems, Clusters, and the Knowledge Economy. *Industrial and Corporate Change*, *10*(4), 945–974. https://doi.org/10.1093/icc/10.4.945

Cubaud, P., Dupire, J., & Topol, A. (2005). Digitization and 3D modeling of movable books. *Proceedings of the ACM/IEEE Joint Conference on Digital Libraries*, *1624*, 244–245. https://doi.org/10.1145/1065385.1065440

Dearing, E., & Hamilton, L. C. (2006). Contemporary advances and Classic Advice for Analyzing Mediating and Moderating Variables. *Monographs of the Society for Research in Child Development*, *71*, 88–104. https://doi.org/10.1111/j.1540-5834.2006.00406.x

Dehn, D. M., & Van Mulken, S. (2000). Impact of animated interface agents: a review of empirical research. *International Journal of Human Computer Studies*, *52*(1), 1–22. https://doi.org/10.1006/ijhc.1999.0325

Denis, H. D., & Pereira, L. N. (2014). Measuring the level of endorsement of the New Environmental Paradigm: a transnational study. *Dos Algarves: A Multidisciplinary e-Journal*, (23), 4–26. Retrieved from http://www.dosalgarves.com/rev/N23/1rev23.pdf

Deutsches BiomasseForschungsZentrum. (2012). *Monitoring zur Wirkung des Erneuerbare-Energien-Gesetz (EEG) auf die Entwicklung der Stromerzeugung aus Biomasse.* Berlin.

Dohmen, T., Falk, A., Huffman, D., & Sunde, U. (2007). Are risk aversion and impatience related to cognitive ability? *American Economic Review*, *100*(3), 1238–1260. https://doi.org/10.1257/aer.100.3.1238

Donges, U. S., Kersting, A., & Suslow, T. (2012). Women's greater ability to perceive happy facial emotion automatically: Gender differences in affective priming. *PLoS ONE*, *7*(7), 1–5. https://doi.org/10.1371/journal.pone.0041745

Downs, J. S., Loewenstein, G., & Wisdom, J. (2009). Strategies for Promoting Healthier Food Choices on JSTOR. *American Economic Review: Papers & Proceedings*, *99*(2), 159–164. https://doi.org/10.1257/aer.99.2.159

Dreyfus, H. L., & Dreyfus, S. E. (1991). Making a Mind Versus Modelling the Brain: Artificial Intelligence Back at the Branchpoint. In *Understanding the Artificial: On the Future Shape of Artificial Intelligence* (pp. 33–54). London: Springer London. https://doi.org/10.1007/978-1-4471-1776-6_3

Drichoutis, A. C., Nayga Jr., R. M., & Lazaridis, P. (2009). Can Nutritional Label Use Influence Body Weight Outcomes? *Kyklos*, *62*(4), 500–525. https://doi.org/10.1111/j.1467-6435.2009.00448.x

Dunlap, R. E., Van Liere, K. D., Mertig, A. G., & Jones, R. E. (2000). New Trends in Measuring Environmental Attitudes: Measuring Endorsement of the New Ecological Paradigm: A Revised NEP Scale. *Journal of Social Issues*, *56*(3), 425–442. https://doi.org/10.1111/0022-4537.00176

Ebel, B., Mijanovich, T., Dixon, B., Abrams, C., Weitzman, B., Kersh, R., … Odedegbe, G. (2013). Calorie Labeling, Fast Food Purchasing and Restaurant Visits. *Obesity*, *21*(11), 2172–2179. https://doi.org/10.1038/nn.2665.An

Ehrhardt-Martinez, A. K., & Donnelly, K. a. (2010). Advanced Metering Initiatives and Residential Feedback Programs: A Meta-Review for Household Electricity-Saving Opportunities. *Energy*, *123*(6), 128.

Enders, C. K., & Tofighi, D. (2007). Centering Predictor Variables in Cross-Sectional Multilevel Models: A New Look at an Old Issue. *Psychological Methods*, *12*(2), 121–138. https://doi.org/10.1037/1082-989X.12.2.121

European Commission. (2013). *Accompanying the document: Cost-benefit analyses & state of play of smart metering deployment in the EU-27 Accompanying the document Report from the Commission Benchmarking smart metering deployment in the EU-27 with a focus on electricity*. Brussels. Retrieved from http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A52014SC0189

European Commission. (2014). *Benchmarking smart metering deployment in the EU-27 with a focus on electricity*. *European Commision*. Brussels. Retrieved from https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=COM%3A2014%3A356%3AFIN

European Union. (2009). Directive of 2009/72/EC of the European Parliament and of the Council of 13 July 2009 Concerning Common Rules for the Internal Market in Electricity and Repealing Directive 2003/54/EC. *Official Journal of the European Union*, *L211*(August), L 211/55-L 211/93. Retrieved from https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=celex%3A32009L0072

Fang, X., Misra, S., Xue, G., & Yang, D. (2012). Smart Grid — The New and Improved Power Grid: A Survey. *IEEE Communications Surveys & Tutorials*, *14*(4), 944–980. https://doi.org/10.1109/SURV.2011.101911.00087

Follows, S. B., & Jobber, D. (2000). Environmentally responsible consumer model. *European*

Journal of Marketing, *34*(5), 1–24. https://doi.org/10.1108/03090560010322009

Frondel, M., Ritter, N., & Sommer, S. (2015). *Stromverbrauch privater Haushalte in Deutschland: Eine ökonometrische Analyse* (RWI Materialien No. 92). Essen.

Gans, W., Alberini, A., & Longo, A. (2013). Smart meter devices and the effect of feedback on residential electricity consumption: Evidence from a natural experiment in Northern Ireland. *Energy Economics*, *36*, 729–743. https://doi.org/10.1016/J.ENECO.2012.11.022

Gehl, R. W. (2013). What's on your mind? Social media monopolies and noopower. *First Monday*, *18*(3). https://doi.org/10.5210/fm.v18i3.4618

Geliebter, A., & Aversa, A. (2003). Emotional eating in overweight, normal weight, and underweight individuals. *Eating Behaviors*, *3*(4), 341–347.

Gerend, M. A. (2009). Does Calorie Information Promote Lower Calorie Fast Food Choices Among College Students? *Journal of Adolescent Health*, *44*(1), 84–86. https://doi.org/10.1016/j.jadohealth.2008.06.014

Gerpott, T. J., & Paukert, M. (2013). Determinants of willingness to pay for smart meters: An empirical analysis of household customers in Germany. *Energy Policy*, *61*, 483–495. https://doi.org/10.1016/j.enpol.2013.06.012

Ghaoui, C. (2006). *Encyclopedia of Human Computer Interaction*. London: Idea Group Reference. https://doi.org/10.4018/978-1-59140-562-7

Gillen, G., Vitt, Ju., & Bünding, M. (2011). *Information gut, alles gut ?* Berlin. Retrieved from https://www.vzbv.de/sites/default/files/mediapics/verbraucherinformationen_wirksam_empfehlungen_vzbv.pdf

Gottschalk, I. (2001). *Ökologische Verbraucherinformation: Grundlagen, Methoden und Wirkungschancen.* Berlin: Duncker & Humblot.

Graf, A., & Schneider, H. (2016). *The E-Commerce Book: About a Channel that became an*

Industry: Amazon.de (1st ed.). North Charleston, South Carolina: CreateSpace Independent Publishing Platform.

Grunert, K. G., & Wills, J. M. (2007). A review of European research on consumer response to nutrition information on food labels. *Journal of Public Health*, *15*(5), 385–399. https://doi.org/10.1007/s10389-007-0101-9

Ha-Brookshire, J. E., & Hodges, N. N. (2009). Socially Responsible Consumer Behavior? Exploring Used Clothing Donation Behavior. *Clothing & Textiles Research Journal*, *27*, 179–196. https://doi.org/10.1177/0887302X08327199

Hagberg, J., Sundstrom, M., & Egels-Zandén, N. (2016). The digitalization of retailing: an exploratory framework. *International Journal of Retail and Distribution Management*, *44*(7), 694–712. https://doi.org/10.1108/IJRDM-09-2015-0140

Hellmann, K.-U. (2018). Leitbilder, Erlebnisse und die mentale Dimension des modernen Konsums: zum Menschenbild der akademischen Verbraucherforschung. In C. Bela & W. Schuldizniski (Eds.), *Jenseits des Otto Normalverbrauchers: Verbraucherpolitik in Zeiten des "unmanagable consumer" . Beiträge zur Verbraucherforschung 8* (pp. 19–51). Düsseldorf: Verbraucherzentrale. https://doi.org/10.15501/978-3-86336-920-0_2

Hensher, D. A., Rose, J. M., & Greene, W. H. (2015). *Applied Choice Analysis* (2nd Ed.). Cambridge: Cambridge University Press.

Hess, S., & Hensher, D. A. (2010). Using conditioning on observed choices to retrieve individual-specific attribute processing strategies. *Transportation Research Part B: Methodological*, *44*(6), 781–790. https://doi.org/10.1016/J.TRB.2009.12.001

Hewitt, J. A., & Hanemann, W. M. (1995). A Discrete/Continuous Choice Approach to Residential Water Demand under Block Rate Pricing. *Land Economics*, *71*(2), 173. https://doi.org/10.2307/3146499

Hofacker, C. (2007). *Mathematical Marketing*. Florida: New South Network Services.

Hubert, Feinleib, McNamara, & Castelli. (1983). Obesity as an independent risk factor for cardiovascular disease: a 26- year follow-up of participants in the Framingham Heart Study. *Circulation*, *67*(5), 968–977. https://doi.org/10.1161/01.CIR.67.5.968

Hwang, C.-L., & Yoon, K. (1981). *Methods for Multiple Attribute Decision Making*. Berlin: Springer. https://doi.org/10.1007/978-3-642-48318-9_3

Ida, T., Murakami, K., & Tanaka, M. (2014). A stated preference analysis of smart meters, photovoltaic generation, and electric vehicles in Japan: Implications for penetration and GHG reduction. *Energy Research & Social Science*, *2*, 75–89. https://doi.org/10.1016/j.erss.2014.04.005

James, A., Adams-Huet, B., & Shah, M. (2015). Menu labels displaying the kilocalorie content or the exercise equivalent: Effects on energy ordered and consumed in young adults. *American Journal of Health Promotion*, *29*(5). https://doi.org/10.4278/ajhp.130522-QUAN-267

Janiszewski, C., & Cunha, M. (2004). The Influence of Price Discount Framing on the Evaluation of a Product Bundle. *Journal of Consumer Research*, *30*(4), 534–546. https://doi.org/10.1086/380287

Kahneman, D., & Frederick, S. (2005). A Model of Heuristic Judgement. In K. Holyoak & R. G. Morrison (Eds.), *The Cambridge Handbook of Thinking and Reasoning* (pp. 267–294). Cambridge, UK: Cambridge University Press.

Kahnemann, D. (2011). *schnelles Denken, langsames Denken*. München: Siedler Verlag. https://doi.org/10.1007/s13398-014-0173-7.2

Kaufmann, S., Künzel, K., & Loock, M. (2013). Customer value of smart metering: Explorative evidence from a choice-based conjoint study in Switzerland. *Energy Policy*, *53*, 229–239. https://doi.org/10.1016/j.enpol.2012.10.072

Keller, C., Markert, F., & Bucher, T. (2015). Nudging product choices: The effect of position change on snack bar choice. *Food Quality and Preference, 41*, 41–43. https://doi.org/10.1016/j.foodqual.2014.11.005

Kenkel, D. S. (1991). Health Behavior, Health Knowledge, and Schooling. *Journal of Political Economy*, *99*(2), 287–305. https://doi.org/Doi 10.1086/261751

Kennedy, J. F. (1961). *Public Papers of the Presidents of the United States. Containing the Public Messages, Speeches, and Statements of the President, January 20 to December 31, 1961*. Washington: U.S. Government Printing Office.

Kim, W. C., & Mauborgne, R. (1999). Strategy, value innovation, and the knowledge economy. *Sloan Management Review*, *40*(3), 41. https://doi.org/10.1086/250095

Kiszko, K. M., Martinez, O. D., Abrams, C., & Elbel, B. (2014). The influence of calorie labeling on food orders and consumption: A review of the literature. *Journal of Community Health*, *39*(6), 1248–1269. https://doi.org/10.3174/ajnr.A1256.Functional

Köster, E. P., & Mojet, J. (2015). From mood to food and from food to mood: A psychological perspective on the measurement of food-related emotions in consumer research. *Food Research International*, *76*(P2), 180–191. https://doi.org/10.1016/j.foodres.2015.04.006

Krishnamurti, T., Schwartz, D., Davis, A., Fischhoff, B., de Bruin, W. B., Lave, L., & Wang, J. (2012). Preparing for smart grid technologies: A behavioral decision research approach to understanding consumer expectations about smart meters. *Energy Policy*, *41*, 790–797. https://doi.org/10.1016/j.enpol.2011.11.047

Kroh, M., Brücker, H., Kühne, S., Liebau, E., Schupp, J., Siegert, M., & Trübswetter, P. (2016). *SOEP Survey Papers Series C – Data Documentation*. Berlin: DIW Berlin. https://doi.org/10.5684/soep.iab-bamf-soep-ref.2016

Kuhlmann, E. (1990). *Verbraucherpolitik - Grundzüge ihrer Theorie und Praxis*. München: F.

Vahlen.

L. Milkman, K., Chugh, D., & Bazerman, M. H. (2008). How Can Decision Making Be Improved ? How Can Decision Making Be Improved ? *Perspectives on Psychological Science*, *4*, 379–383. https://doi.org/10.2307/40645704

Lancaster, K. J. (1966). A New Approach to Consumer Theory. *Source Journal of Political Economy*, *74*(2), 132–157. Retrieved from http://www.jstor.org/stable/1828835

Lange, H. (2008). *Nachhaltigkeit als radikaler Wandel. Die Quadratur des Kreises?* Wiesbaden: VS, Verl. für Sozialwiss.

Larson, N., Neumark-Sztainer, D., Laska, M. N., & Story, M. (2011). Young adults and eating away from home: associations with dietary intake patterns and weight status differ by choice of restaurant. *Journal of American Dietetic Association*, *111*(11), 1696–1703. https://doi.org/10.1109/TMI.2012.2196707.Separate

Lassen, A. D., Lehmann, C., Andersen, E. W., Werther, M. N., Thorsen, A. V., Trolle, E., … Tetens, I. (2016). Gender differences in purchase intentions and reasons for meal selection among fast food customers – Opportunities for healthier and more sustainable fast food. *Food Quality and Preference*, *47*, 123–129. https://doi.org/10.1016/J.FOODQUAL.2015.06.011

Laukkanen, T., Sinkkonen, S., Kivijärvi, M., & Laukkanen, P. (2007). Innovation resistance among mature consumers. *Journal of Consumer Marketing*, *24*(7), 419–427. https://doi.org/10.1108/07363760710834834

Lawton, S. (2016). *Linking the New Ecological Paradigm Scale to How Pro-Environmental Behavior is Developed*. University of Nebraska Lincoln.

Lehdonvirta, V. (2012). A history of the digitalization of consumer culture : From Amazon through Pirate Bay to FarmVille. In J. D. Molesworth, M. and Knott (Ed.), *Digital Virtual*

Consumption (pp. 2–30). London: Routledge. https://doi.org/10.4324/9780203114834

Lehner, M., Mont, O., & Heiskanen, E. (2015). Nudging – A promising tool for sustainable consumption behaviour? *Journal of Cleaner Production*, *134 Part A*, 166–177. https://doi.org/10.1016/j.jclepro.2015.11.086

Leu Jr, D. J. J., Kinzer, C. K. K., From, N. L. E., Information, O., Coiro, J., Cammack, D. W. W., & Technologies, C. (2004). Toward a Theory of New Literacies Emerging From the Internet and Other Information and Communication Technologies. *Reading Research Quarterly*, *5*(2000), 1570–1613. https://doi.org/Article

Levi, A., Chan, K. K., & Pence, D. (2006). Real men do not read labels: The effects of masculinity and involvement on college students' food decisions. *Journal of American College Health*, *55*(2), 91–98. https://doi.org/10.3200/JACH.55.2.91-98

Liao, S. M., Sandberg, A., & Roache, R. (2012). Human Engineering and Climate Change. *Ethics, Policy and Environment*, *15*(2), 206–221. https://doi.org/10.1080/21550085.2012.685574

Lis, B. (2013). In eWOM we trust: A framework of factors that determine the eWOM credibility. *Business and Information Systems Engineering*, *5*(3), 129–140. https://doi.org/10.1007/s12599-013-0261-9

Lis, B., & Neßler, C. (2014). Electronic Word of Mouth. *Business & Information Systems Engineering*, *56*(1), 63–65. https://doi.org/10.1007/s11576-013-0398-7

Liu, X., He, M., Gao, F., & Xie, P. (2008). An empirical study of online shopping customer satisfaction in China: a holistic perspective. *International Journal of Retail & Distribution Management*, *36*(11), 919–940. https://doi.org/10.1108/09590550810911683

Long, M. W., Tobias, D. K., Cradock, A. L., Batchelder, H., & Gortmaker, S. L. (2015). Systematic review and meta-analysis of the impact of restaurant menu calorie labeling.

American Journal of Public Health, *105*(5), e11–e24. https://doi.org/10.2105/AJPH.2015.302570

Louviere, J., Hensher, D. A., & Swait, J. (2000). *Stated choice methods: Analysis and applications*. Cambridge: Cambridge University Press.

Louviere, J., Street, D., Carson, R., Ainslie, A., Deshazo, J. R., Cameron, T., … Kohn, R. (2002). Dissecting the random component of utility. *Marketing Letters*, *13*(3), 177–193. https://doi.org/10.1023/A:1020258402210

Lyman, B. (1982). The nutritional value and food group characteristics of foods preferred during various emotions. *Journal of Psychology*, *112*, 121–127.

Macht, M., & Simons, G. (2000). Emotions and eating in everyday life. *Appetite*, *35*(1), 65–71. https://doi.org/10.1006/appe.2000.0325

Manski, C. (1977). The Structure of Random Utility Models. *Theory and Decision*, *8*(3), 229–254.

Marette, S., Roosen, J., Bieberstein, A., Blanchemanche, S., & Vandermoere, F. (2009). Impact of Environmental, Societal and Health Information on Consumers' Choices for Nanofood. *Journal of Agricultural & Food Industrial Organization*, *7*(2). https://doi.org/10.2202/1542-0485.1274

Marteau, T. M., Ogilvie, D., Roland, M., Suhrcke, M., & Kelly, M. P. (2011). Judging nudging: Can nudging improve population health? *BMJ*, *342*(7791), 263–265. https://doi.org/10.1136/bmj.d228

Martínková, N., Nová, P., Sablina, O. V., Graphodatsky, A. S., & Zima, J. (2004). Karyotypic relationships of the Tatra vole (Microtus tatricus). *Folia Zoologica*, *53*(3), 279–284. https://doi.org/10.1007/s13398-014-0173-7.2

Maynes, E. S., & Assum, T. (1982). Informationally Imperfect Consumer Markets: Empirical

Finding and Policy Implications. *The Journal of Consumer Affairs*, *16*(1), 62–87. https://doi.org/10.2307/23859086

Mela, D. J. (2001). Determinants of Food Choice: Relationships with Obesity and Weight Control. *Obesity Research*, (Supplement 4), 249S–255S. https://doi.org/10.1038/oby.2001.127

Mensink, G. B. M., Schienkiewitz, A., Haftenberger, M., Lampert, T., Ziese, T., & Scheidt-Nave, C. (2013). Overweight and obesity in Germany. *Bundesgesundheitsblatt - Gesundheitsforschung - Gesundheitsschutz*, *56*(5–6), 786–794. https://doi.org/10.1007/s00103-012-1656-3

Micklitz, H.-W., Oehler, A., Piorkowsky, M.-B., Reisch, L. A., & Strünck, C. (2010). *Der vertrauende, der verletzliche oder der verantwortungsvolle Verbraucher? Plädoyer für eine differenzierte Strategie in der Verbraucherpolitik: Plädoyer für eine differenzierte Strategie in der Verbraucherpolitik; Stellungnahme d. wiss. Beirats d. BMELV*. Berlin.

Missbach, B., & König, J. S. (2016). Middle choice preference and snack choice: The role of self-regulatory resources to nudge healthier food choice. *Food Quality and Preference*, *53*, 127–131. https://doi.org/10.1016/j.foodqual.2016.06.007

Moens, G. A. (2015). Improving Public Health through Behavioural Rules: A Legitimate Legislative Project? *Procedia - Social and Behavioral Sciences*, *211*, 1096–1105. https://doi.org/10.1016/j.sbspro.2015.11.146

Momoh, J. (2012). *Smart Grid: Fundamentals of Design and Analysis*. New York City: Wiley. https://doi.org/10.1002/9781118156117

Montagne, B., Kessels, R. P. C., Frigerio, E., De Haan, E. H. F., & Perrett, D. I. (2005). Sex differences in the perception of affective facial expressions: Do men really lack emotional sensitivity? *Cognitive Processing*, *6*(2), 136–141. https://doi.org/10.1007/s10339-005-0050-

6

Morse, K. L., & Driskell, J. A. (2009). Observed sex differences in fast-food consumption and nutrition self-assessments and beliefs of college students. *Nutrition Research*, *29*(3), 173–179. https://doi.org/10.1016/j.nutres.2009.02.004

Müller, E., & Mackert, H. (2003). Bildung für Haushalt und Konsum als vorsorgender Verbraucherschutz. *Aus Politik Und Zeitgeschichte*, *B9*, 20–26.

Naus, J., Spaargaren, G., Van Vliet, B. J. M., & Van der Horst, H. M. (2014). Smart grids, information flows and emerging domestic energy practices. *Energy Policy*, *68*, 436–446. https://doi.org/10.1016/j.enpol.2014.01.038

Nielsen, S. J., Siega-Riz, A. M., & Popkin, B. M. (2002). Trends in food locations and sources among adolescents and young adults. *Preventive Medicine*, *35*(2), 107–113. https://doi.org/10.1006/pmed.2002.1037

O'Donoghue, T., & Rabin, M. (1999). Doing It Now or Later. *The American Economic Review*, *89*(1), 103–124.

O'Leary, D. E. (2013). Artificial Intelligence and Big Data. *IEEE Intelligent Systems*, *28*(2), 96–99. https://doi.org/10.1109/MIS.2013.39

Osburn, C. B. (2014). The Control Revolution: Technological and Economic Origins of the Information Society (Book Review). *College & Research Libraries*, *49*(1), 89–90. https://doi.org/10.5860/crl_49_01_89

Paatsch, W. (2016). Energy turnaround – a challenge for surface technology. *Transactions of the Institute of Metal Finishing*, *94*(5), 228–230. https://doi.org/10.1080/00202967.2016.1209295

Paetz, A.-G., Dütschke, E., & Fichtner, W. (2012). Smart Homes as a Means to Sustainable Energy Consumption: A Study of Consumer Perceptions. *Journal of Consumer Policy*, *35*(1), 23–41. https://doi.org/10.1007/s10603-011-9177-2

Park, C. K., Kim, H. J., & Kim, Y. S. (2014). A study of factors enhancing smart grid consumer engagement. *Energy Policy*, *72*, 211–218. https://doi.org/10.1016/j.enpol.2014.03.017

Patel, K. A., & Schlundt, D. G. (2001). Impact of moods and social context on eating behavior. *Appetite*, *36*(2), 111–118. https://doi.org/10.1006/appe.2000.0385

Poole, A., & Ball, L. J. (2006). Eye Tracking in HCI and Usability Research: Current status and future prospects. In C. Ghaoui (Ed.), *Encyclopedia of Human Computer Interaction* (pp. 211–219). Hershey, Pennsylvania: IGI Global. https://doi.org/10.4018/978-1-59140-562-7.ch034

Rajagopalan, S. R., Sankar, L., Mohajer, S., & Poor, H. V. (2011). Smart meter privacy: A utility-privacy framework. In *2011 IEEE International Conference on Smart Grid Communications* (pp. 190–195). IEEE. https://doi.org/10.1109/SmartGridComm.2011.6102315

Reid Chassiakos, Y., Radesky, J., Christakis, D., Moreno, M. A., & Cross, C. (2016). Children and Adolescents and Digital Media. *PEDIATRICS*, *138*(5), e20162593–e20162593. https://doi.org/10.1542/peds.2016-2593

Reisch, L. (2003). Strategische Grundsätze und Leitbilder einer neuen Verbraucherpolitik Diskussionspapier des Wissenschaftlichen Beirats für Verbraucher- und Ernährungspolitik beim BMVEL. *Verbraucher Und Recht*, *18*(11), 34.

Rich, C. S. (1997). The political economy of international environmental cooperation: Santa Cruz, California, 3-4 June 1996. *ICGG Policy Papers*, *29*(June 1996), 99.

Rising, C. J., & Bol, N. (2017). Nudging Our Way to a Healthier Population: The Effect of Calorie Labeling and Self-Control on Menu Choices of Emerging Adults. *Health Communication*, *32*(8), 1032–1038. https://doi.org/10.1080/10410236.2016.1217452

Roberto, C. A., & Khandpur, N. (2014). Improving the design of nutrition labels to promote healthier food choices and reasonable portion sizes. *International Journal of Obesity*, *38*(SUPPL. 1), S25–S33. https://doi.org/10.1038/ijo.2014.86

Rosenheck, R. (2008). Fast food consumption and increased caloric intake: a systematic review of a trajectory towards weight gain and obesity risk. *Obesity Reviews*, *9*(6), 535–547. https://doi.org/10.1111/j.1467-789X.2008.00477.x

Scheibe, S., & Blanchard-Fields, F. (2009). Effects of regulating emotions on cognitive performance: what is costly for young adults is not so costly for older adults. *Psychology and Aging*, *24*(1), 217–223. https://doi.org/10.1037/a0013807

Scherhorn, G. (1973). *Gesucht: der mündige Verbraucher: Grundlagen eeines verbraucherpolitischen Bildungs- und Informationssystems*. Düsseldorf: Droste.

Schultz, P. W., Nolan, J. M., Cialdini, R. B., Goldstein, N. J., & Griskevicius, V. (2007). Research Article: The Constructive, Destructive, and Reconstructive Power of Social Norms. *Psychological Science*, *18*(5), 429. https://doi.org/10.1111/j.1467-9280.2007.01917.x

Scrinis, G., & Parker, C. (2016). Front-of-Pack Food Labeling and the Politics of Nutritional Nudges. *Law and Policy*, *38*(3), 234–249. https://doi.org/10.1111/lapo.12058

Seward, M. W., Block, J. P., & Chatterjee, A. (2016). A Traffic-Light Label Intervention and Dietary Choices in College Cafeterias. *American Journal of Public Health*, *106*(10), 1808–1814. https://doi.org/10.1126/science.1249098.Sleep

Shocker, A. D., Ben-Akiva, M., Boccara, B., & Nedungadi, P. (1991). Consideration Set Influences on Consumer Decision-Making and Choice: Issues , Models , and Suggestions. *Marketing Letters*, *2*(3), 181–197. https://doi.org/10.1007/BF00554125

Simon, H. A. (1972). Theories of bounded rationality (chapter 8). In C. B. McGuire & R. Radner

(Eds.), *Studies in mathematical and managerial economics*. Amsterdam: North-Holland Pub. Co.

Simon, H. A. (1979). Rational Decision Making in Business Organizations. *The American Economic Review*, *69*(4), 493–513. https://doi.org/10.2307/1808698

Sovacool, B. K. (2014). What are we doing here? Analyzing fifteen years of energy scholarship and proposing a social science research agenda. *Energy Research and Social Science*, *1*, 1–29. https://doi.org/10.1016/j.erss.2014.02.003

Stigler, G. J., & Becker, G. S. (1977). De gustibus non est disputatum. *American Economic Review*, *67*(2), 76–90. https://doi.org/10.1093/nq/s8-VI.144.257-b

Tangney, J. P., Baumeister, R. F., & Boone, A. L. (2004). High self-control predicts good adjustment, less pathology, better grades, and interpersonal success. *Journal of Personality*, *72*(2), 271–324. https://doi.org/10.1111/j.0022-3506.2004.00263.x

Thaler, R. H., & Sunstein, C. B. (2008). *Nugde: Improving Decisions about Health, Wealth and Happiness*. London: Penguin Books.

The Climate Group. (2008). SMART 2020 : Enabling the low carbon economy in the information age. *The Climate Group*, *30*(2), 1–87. https://doi.org/10.1111/j.2006.0906-7590.04873.x

Thorndike, A. N., Riis, J., Sonnenberg, L. M., & Levy, D. E. (2014). Traffic-light labels and choice architecture: Promoting healthy food choices. *American Journal of Preventive Medicine*, *46*(2), 143–149. https://doi.org/10.1016/j.amepre.2013.10.002

Thurstone, L. L. (1927). A law of comparative judgment. *Psychological Review*, *34*(4), 273–286. https://doi.org/10.1037/h0070288

Thurstone, L. L. (1987). Psychophysical analysis. By L. L. Thurstone, 1927. *The American Journal of Psychology*, *100*(3–4), 587–609. https://doi.org/10.2307/1422696

Train, K. E. (2009). *Discrete choice methods with simulation, second edition*. Cambridge:

Cambridge University Press. https://doi.org/10.1017/CBO9780511805271

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty : Heuristics and Biases. *Science*, *185*(4157), 1124–1131. https://doi.org/10.1126/science.185.4157.1124

Umwelt Bundesamt. (2017). Energieverbrauch privater Haushalte. Last accessed February 20, 2019. Retrieved February 19, 2019, from https://www.umweltbundesamt.de/daten/private-haushalte-konsum/wohnen/energieverbrauch-privater-haushalte

Vasiljevic, M., Pechey, R., & Marteau, T. M. (2015). Making food labels social: The impact of colour of nutritional labels and injunctive norms on perceptions and choice of snack foods. *Appetite, 91*, 56–63. https://doi.org/10.1016/j.appet.2015.03.034

Verbraucherzentrale Bundesverband, V. (2015). Intelligente Stromzähler für Privathaushalte. Last accessed February 20, 2019. Retrieved June 11, 2018, from https://www.vzbv.de/dokument/intelligente-stromzaehler-fuer-privathaushalte

Wallenborn, G., Orsini, M., & Vanhaverbeke, J. (2011). Household appropriation of electricity monitors. *International Journal of Consumer Studies*, *35*(2), 146–152. https://doi.org/10.1111/j.1470-6431.2010.00985.x

Wang, S., Yu, D., & Yu, J. (2015). A coordinated dispatching strategy for wind power rapid ramp events in power systems with high wind power penetration. *International Journal of Electrical Power & Energy Systems, 64,* 986–995. https://doi.org/10.1016/J.IJEPES.2014.08.019

Wardle, J., Haase, A. M., & Steptoe, A. (2006). Body image and weight control in young adults: International comparisons in university students from 22 countries. *International Journal of Obesity*, *30*(4), 644–651. https://doi.org/10.1038/sj.ijo.0803050

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social*

Psychology, *54*(6), 1063–1070. https://doi.org/10.1037/0022-3514.54.6.1063

Will Crescioni, A., Ehrlinger, J., Alquist, J. L., Conlon, K. E., Baumeister, R. F., Schatschneider, C., & Dutton, G. R. (2011). High trait self-control predicts positive health behaviors and success in weight loss. *Journal of Health Psychology*, *16*(5), 750–759. https://doi.org/10.1177/1359105310390247

Wilson, A. L., Buckley, E., Buckley, J. D., & Bogomolova, S. (2016). Nudging healthier food and beverage choices through salience and priming. Evidence from a systematic review. *Food Quality and Preference*, *51*, 47–64. https://doi.org/10.1016/j.foodqual.2016.02.009

Windhoff-Héritier, A., Knill, C., & Mingers, S. (1996). *Ringing the changes in Europe : regulatory competition and the transformation of the state : Britain, France, Germany (de Gruyter Studies in Organization, Band 74).* Berlin: Walter de Gruyter.

Wisdom, J., Downs, J. S., & Loewenstein, G. (2010). Promoting healthy choices: Information versus convenience. *American Economic Journal: Applied Economics*, *2*(2), 164–178. https://doi.org/10.1257/app.2.2.164

Zheng, Y., Manson, J. E., Yuan, C., Liang, M. H., Grodstein, F., Stampfer, M. J., … Hu, F. B. (2017). Associations of Weight Gain From Early to Middle Adulthood With Major Health Outcomes Later in Life. *Jama*, *318*(3), 255. https://doi.org/10.1001/jama.2017.7092

Appendices

Appendix 1: Information for participants concerning smart electricity meters (Essay I)

Introductory text smart meters and smart grids with links

First screen

In the following you will read some information about smart meters. The text contains several parts marked in blue. If you are interested in one or more of the topics mentioned there, simply click on the marking and you will be forwarded to a more detailed text. Please feel free to read as many explanations as you like and do so as long as you want. When you have finished reading you can return to the home screen by simply clicking the capital **X** on the top right.

Second screen

Smart meters measure current consumption of electricity every minute. These consumption values are saved and therefore can show user when and how much electricity they use.

This information can also be displayed graphically. Additionally, there are other possibilities to informatively display consumption of electricity.

Another function of smart meters results from their capability to communicate with the power supplier and to receive commands from it. This enables the power supplier to display on a screen of the smart meter whether electricity is offered at the regular or at a discounted rate. The reason for the ability to offer electricity at different times at different rates is explained by the renewable energy sector, through which the electricity network utilization can fluctuate. As a result, for power suppliers it becomes beneficial to offer load-flexible tariffs. The usage of smart homes therefore leads to a changing cost structure when it comes to electricity usage.

Moreover, smart homes offer the possibility to automatically turn on household appliances (like washing machine, dishwasher, water heater) whenever low-priced electricity is available. To do so, there have to be smart devices which are connected to the smart meter.

For the user, this scenario leads to different levels of personal control which, however, can be chosen freely according to the type of use of the smart meter.

On the other hand, the usage of smart meters has positive effects on the environment.

Further questions resulting from communication between smart meters and utilities and between household appliances concern data security and radiation.

Further possibilities of informatively displaying current electricity usage:

The display on the smart meter includes at least the current consumption of electricity. Through this, you can have a closer look to detect possible energy guzzlers and get information about electricity usage of your gadgets in standby mode. The display can either be shown at the smart meter itself or on a computer screen. Displaying the results on a computer screen offers several advantages: energy usage can be shown over a longer period of time (e. g., weeks/months) to show potential for savings. Such a display is also possible for individual rooms and within rooms also for single appliances/groups of appliances. With this you can compare for example costs of entertainment electronics with lighting costs throughout the day. On your personal computer you can also access electricity usage remotely through a password-protected portal. When you are on holidays, for example, you can easily check whether you turned off all lights before departure or whether your neighbor who is in charge of your plants forgot to turn off the lights.

Load-flexible tariffs:

Load-regulated electricity tariffs are tariffs that offer electricity at different times at different rates. As opposed to classical night tariffs where electricity rates change according to fixed time slots, with load-regulated tariffs the rate depends on the current usage of the electricity grid: if much electricity is produced by renewable energy sources like wind power plants and solar panels, electricity can be offered at a lower rate. Therefore, with such a tariff, consumers have a financial incentive to postpone high-consumption activities to time slots when electricity is offered at a lower rate.

There is also the possibility to display energy usage on smart homes using a traffic light system. Another possibility is to offer appliances that are connected to smart meters. They can be activated automatically as soon as the electricity tariff has switched to a lower rate. To do so, the user would have to load e. g., his washing machine and set it accordingly so that the washing cycle is only started when there is electricity at a lower rate available.

There is a guarantee that at least once a day there will be lower-priced electricity available, probably even multiple times a day.

Changing cost structure:

Smart homes use your internet connection at home to periodically receive encrypted signals from energy suppliers. These signals make it possible to show the consumer at home whether electricity is offered at normal or at a discounted rate. Furthermore, smart meters themselves send signals to their energy suppliers. By doing so, the energy supplier can adjust the energy bill so that it only shows actual consumption. Payments in advance and subsequent payments become redundant. Communication is established either via internet or via a weak radio signal which allows wireless reading of the meter status through a passing car. Both possibilities have an effect on the radiation that is produced by your smart meter.

Smart devices:

Smart devices/appliances can communicate with smart meters. It becomes possible to benefit from a flexible electricity tariff with relatively low effort. Flexible electricity tariffs offer electricity at a cheaper rate when there is much electricity available from renewable energy sources.

Smart meters can show the user when there is a change in the electricity tariff. Moreover, this can be reported automatically to smart devices that are connected to the smart meter.

For instance, if the washing machine is connected to the smart meter via Wi-Fi, it can start the washing cycle as soon as electricity is offered at a cheaper rate.

To do so, the user simply has to load the washing machine, set it to the right mode and therefore can "automatically" benefit from cheaper electricity rates.

Personal control:

The usage of smart meters offers the consumer the possibility to benefit from fluctuation in electricity rates. To do so he/she has to pay attention to the display on the smart meter and can do energy-intensive activities like doing the laundry or vacuuming at lower cost. However, this also means that for example the time slot when the washing machine runs depends on the electricity rate. Compared to the "classical" situation in which consumers can do their laundry whenever they want, the use of smart meters in combination with a flexible electricity tariff means a certain loss of autonomy or control.

The same holds when smart devices are included in the described scenario. They offer the possibility to the consumer to automatically postpone energy-intensive procedures to time slots when electricity is offered at a lower rate. This is more comfortable for the consumer, however, there is still a loss of control since now it is not the consumer himself anymore who determines the temporal sequence at home (doing the laundry or the dishes, heating water etc.). In the scenario described, these jobs further depend on the fluctuating electricity rate offered by the energy supplier.

Effects on the environment:

Positive effects on the environment result from the possibility to get detailed information from smart meters about personal electricity consumption (when and where electricity is used). If it is the case that thanks to this information, consumers for example turn off the lights more often or decide to install more energy-efficient devices, a positive effect on the environment occurs.

If many people use smart meters and use electricity when it is offered at lower rates, it also becomes possible to shut down conventional power plants because electricity from renewable energy sources is used instead of theirs.

Data security:

Because of the communication of smart meters with energy suppliers, questions concerning data security arise. Existing data protection guidelines are met in any case. They include encryption of sent and received data and storage at the energy supplier that is not accessible for everyone. Moreover, consumer data must not be sold to third parties.

For some, this legal regulation does not go far enough. They request a higher data protection level for smart meters. This can be achieved through a technical solution which establishes a higher security level for data of smart meters when it comes to remote hacker attacks.

Radiation:

Radiation in terms of radio waves for data transmission arises when smart meters send consumer data to the energy supplier. This happens in a 15-minute interval. On the other hand, smart meters receive a signal from the energy supplier whenever the electricity tariff has been changed.

This radiation emerges either because of the wireless connection to the internet of the household or because of a signal that is sent to wirelessly read the meter status which in turn can be received by a car of the energy supplier that passes by. There is the possibility to reduce the radiation caused by smart meters through higher levels of radiation protection by technical measures. However, these measures are not covered in detail here.

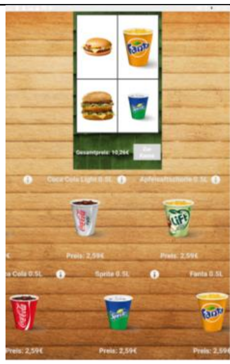
Appendix 2: Selection of dishes along with the respective nutrition information (Essay II)

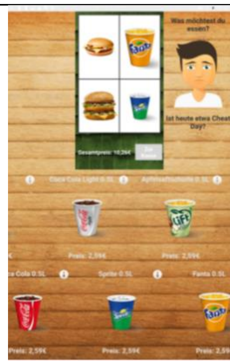
Upper Bar						
		Kilo-calories	Fat*	Protein*	Carbs*	Price in €
Main Dishes	6 Chicken nuggets & sauce	318	14	17	30	3.59
	Chicken wrap	459	24	24	49	4.19
	Large salad with quinoa	210	6	8	5	4.59
	Small cheeseburger	304	12	16	31	1.29
	Salad with dressing	51	1	4	10	3.59
Side Dishes	Fries small with ketchup	265	11	3	29	1.98
	Small salad with dressing	41	1	1	4	1.59
Drinks	Water .5 l	0	0	0	0	2.59
	Coke light .5 l	1	0	0	0	2.59
	Apple spritzer .5 l	125	0	0	30	2.59
Average		186	6.9	7.7	18.8	2.86
Lower Bar						
		Kilo-calories	Fat*	Protein*	Carbs*	Price in €
Main Dishes	Large Cheeseburger	518	28	12	35	4.19
	Double Cheeseburger	509	25	26	42	3.79
	Large Veggie burger	534	38	30	43	4.69
	Large Chicken burger	443	19	20	47	3.71
Side Dishes	Fries medium with ketchup	367	16	4	47	2.48
	Fries large with ketchup	474	21	5	60	2.78
Drinks	Coke .5 l	210	0	0	53	2.59
	Sprite .5 l	185	0	0	46	2.59
	Fanta .5 l	190	0	0	50	2.59
Desert	Ice cream with chocolate	352	18	9	83	2.49
Average		378	16.5	10.6	50.6	3.20

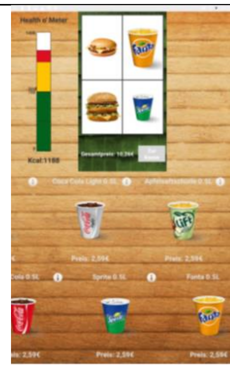
* in grams

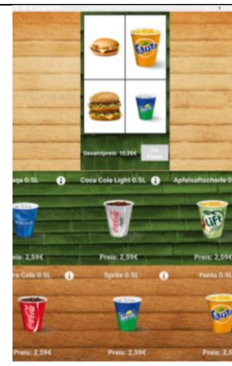
Appendix 3: Images of the ordering screen (Essay II)

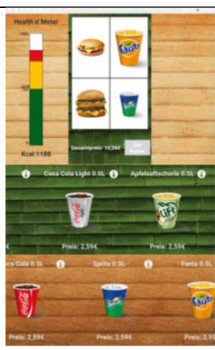
Figure A 3.1
Ordering screen with calorie goal

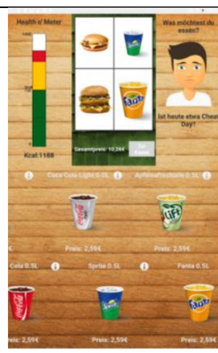

2.2.a. Ordering screen with all features off

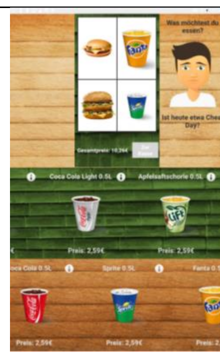

2.2.b. Ordering screen with the feature order assistant on


2.2.c. Ordering screen with the feature traffic light labeling on


2.2.d. Ordering screen with the feature highlighting choices on


2.2.e. Ordering screen with the features highlighting choices and traffic light labeling on


2.2.f. Ordering screen with the features traffic light labeling and order assistant on


2.2.g. Ordering screen with the features order assistant and highlighting choices on


2.2.h. Ordering screen with all features on

Figure A 3.2.
Ordering screen with different combinations of nudging features